2020

# Measuring Quality of Data Collection Process to Ensure Data Quality for Public Health Information Systems

Hong Chen
*University of Wollongong*

UNIVERSITY
OF WOLLONGONG
AUSTRALIA

# Measuring Quality of Data Collection Process to Ensure Data Quality for Public Health Information Systems

Hong Chen

Supervisors:

Associate Professor Ping Yu, Professor David Hailey, Dr Tingru Cui, Professor Ning Wang

This thesis is presented as part of the requirement for the award of the degree of

Doctor of Philosophy

This research has been conducted with the support of the Australian Government Research Training Program Scholarship

University of Wollongong

School of Computing and Information Technology

Faculty of Engineering and Information Sciences

August 2020

This research has been conducted with the support of an Australian Government Research Training Program Scholarship.

# Abstract

**Background:** High quality data and effective data quality assessment are vital for accurate detection and diagnosis of public health risks, for the design, implementation, and evaluation of public health intervention impact and public health outcome measurement. Effective data quality assessment not only reports the status of data quality but also determines the causes of data quality problems. To date, there is scarce research on the quality of the data collection process for public health information systems (PHISs), in which data quality problems frequently occur.

**Aims:** This PhD project aims to develop a framework to evaluate the quality of the PHIS data collection process. The aim is achieved through realizing three research objectives: (1) review and synthesize the existing PHIS data quality assessment methods; (2) conceptualize and validate a framework to measure the quality of the PHIS data collection process; (3) use the developed framework to evaluate the data collection process for a country-level PHIS.

**Methods:** The project systematically reviews PHIS data quality assessment methods and the essential components of the quality of the PHIS data collection process. An expert elicitation research approach is used to qualitatively validate a 4D (data collection management, data collection personnel, data collection environment, data collection system) component framework to evaluate the PHIS data collection process in the context of Chinese National HIV/AIDS Information Management Systems (CRIMS). Evaluation of the quality of the CRIMS data collection process is completed using the validated 4D Framework.

**Results:** A three-dimensional (3D) framework for PHIS data quality assessment is developed, which is comprised of the quality of data, data use, and the data collection process. The dimension of data is the most frequently assessed dimension and there is a lack of attention to the quality of the PHIS data collection process and data use. The major contribution of this research to the PHIS data quality assessment domain is the 4D framework for measuring the quality of the PHIS data collection process which it has created and validated. The validated 4D framework contains four components, 16 subcomponents, and 116 quality indicator statements. The first component, data collection management, includes the subcomponents of data collection protocol and quality assurance, and 41 (35.3%) quality indicator statements. The second component, the data collection environment, consists of six subcomponents: leadership, training, funding, organizational policy, high-level management support, and collaboration among the parallel organizations. It includes 37 (31.9%) quality indicator statements. The third, data collection personnel, has four subcomponents: a perception of data collection, skill and competence, communication, and staffing patterns. It includes 22 (19.0%) quality indicator statements. The fourth component, data collection system, also has four subcomponents: functions, integration of data collection systems, technical support, and devices for data collection. It includes 16 (14%) quality indicator statements. The 116 quality indicator statements are classified into 82 facilitators and 34 barriers according to their direction of influence, positive or negative, on the quality of the PHIS data collection process.

The application of the 4D Framework to evaluate the quality of the HIV/AIDS data collection process in China has identified 65% (75/116) of the quality indicator statements. These include 61% (50/82) of the

facilitators and 74% (25/34) of the barriers of the 4D Framework in action. The CRIMS has achieved better-quality data collection management. The areas for improvement include engaging frontline staff in the design of data collection protocols, standardizing quality assurance procedures, strengthening leadership, recognizing data collector's contributions, and meeting end users' needs for the CRIMS.

**Conclusion:** This PhD project contributes two frameworks in the knowledge domain of PHIS data quality assessment. A 3D framework for data quality assessment, including quality of data, the data collection process and data use, can be used to guide the effort to evaluate PHIS data quality. A 4D framework for measuring the quality of the PHIS data collection process, including data collection management, the data collection environment, data collection personnel and the data collection system, provides an evaluation tool to guide public health efforts in the assessment of the quality of the PHIS data collection process, an integrated component to improve the PHIS data quality.

**Key words:** data quality; data collection process; measurement; public health information systems

# Acknowledgments

I would like to express my greatest appreciation to my supervisors Associate Professor Ping Yu, Professor David Hailey, Dr Tingru Cui and Professor Ning Wang for their expert guidance, constructive criticism, continuing support, and encouragement throughout my doctoral study.

Specifically, I would like to express my gratitude to Associate Professor Ping Yu for her professional knowledge and great effort in directing my research, shaping my way of thinking and improving my research and academic writing skills. I am grateful to Professor David Hailey for bringing his invaluable research experience to the conduct of this research and preparation of my publications and this thesis. I am also grateful to Dr Tingru Cui and Professor Ning Wang for their professional knowledge and great method in directing my research.

Without these commitments, it would not have been possible for me to complete this project. I am indebted to all my co-authors, Associate Professor Ping Yu, Professor David Hailey, Dr Tingru Cui, and Professor Ning Wang, for their invaluable contributions to the publications included in this thesis. I am also deeply grateful to Dr Madeleine Cincotta who so kindly and supportively improved my writing of the papers.

I am indebted to Jiangxi Provincial Center of Disease Control and Prevention for allowing me study leave during my research. Without public health colleagues, healthcare professionals, and health administrators in China participating in my data collection and providing abundant information, there would be no data available to provide evidence of this study.

My thanks also go to my current and past colleagues Siyu Qian, Tao Jiang, Michael Burwood, Xiaojun Zhang, and Ting Song. I appreciate all the time we spent together discussing and sharing ideas.

From the depth of my heart, I thank my loving husband Shuo Liu and daughter Junliang Liu who are always understanding and supportive, regardless of whether I have been successful, experiencing hardships, or feeling happy or down, throughout the period of this PhD study. The project could not be completed without their encouragement.

Finally, this thesis is dedicated to my dear parents Zhijian Chen and Bingmei Liu who have given me endless love during my life.

# Certification

*I, Hong Chen, declare that this thesis submitted in fulfilment of the requirements for the conferral of the degree Doctor of Philosophy, from the University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. This document has not been submitted for qualifications at any other academic institution.*

_____

***Hong Chen***
*20th August 2020*

# Statement of authorship

This thesis is prepared in the style of Thesis by Compilation by the University of Wollongong. Seven papers have been prepared during my PhD study (see List of publications). Chapters 2, 3, 4 and 5 consist of four papers, all published in peer-reviewed journals. The other three published papers have not been included as a chapter in this thesis but are referred to primarily when adding context to the background or findings presented throughout the thesis.

I am the first author of all seven papers. I contributed to the study design, data collection and analysis and preparation of the manuscripts. Details about the seven papers including title, the extent of my contribution to the research and the authorship of each paper, the publication outlet for the manuscripts, and their association with this thesis are identified in Table 1.1. Four co-authors are involved in the publications. They are Ping Yu, David Hailey, Tingru Cui, and Ning Wang. Their contributions are outlined in the co-author contribution declaration form (Appendix C).

In this thesis, tables, figures, references, and appendices are numbered sequentially from Chapter 1 through to Chapter 6 to maintain a uniform PhD thesis style. A synopsis outlining the specific objectives and research methods of each chapter is provided in the introduction chapter, demonstrating the relationship between all aspects of the research. Each of Chapters 2, 3, 4, and 5 has a foreword as linking text to establish the relationship between one chapter and the next.

# List of publications associated with this thesis

The following papers were produced to disseminate the concept and outcomes of the study undertaken by the author during this PhD project. This thesis is formatted as a thesis by compilation.

1. Chen, H., Hailey, D., Wang, N., Yu, P. A review of data quality assessment methods for public health information systems, *International Journal of Environmental Research and Public Health*, 2014, vol. 11(5), pp. 5170-5207.

   **Status: Published**

2. Chen, H., Yu, P., Hailey, D., Cui, T., Identification of the essential components of quality in the data collection process for public health information systems. *Health Informatics Journal*, 2020;26(1): 664-682. doi: 10.1177/1460458219848622.

   **Status: Published**

3. Chen, H., Yu, P., Hailey, D., Cui, T., Validation of 4D components for measuring quality of the public health data collection process: elicitation study. *Journal of Medical Internet Research* 2021;23(4): e17240. doi: 10.2196/17240.

   **Status: Published**

4. Chen, H., Yu, P., Hailey, D., Cui, T., Application of a four-dimensional framework to evaluate the quality of AIDS data collection process in China. *International Journal of Medical Informatics.* 2021;145. PMID: S1386505620303701. doi: 10.1016/j.ijmedinf.2020.104306.

   **Status: Published**

5. Chen, H., Yu, P., Wang, N., Do we have the reliable data? An exploration of data quality for AIDS information system in China. Studies in Health Technology and Informatics 2013, 192(1-2), pp. 1042

   **Status: Published**

6. Chen, H., Yu, P., Hailey, D., Cui, T., Data quality of the Chinese National AIDS information system: A critical review, Studies in Health Technology and Informatics 2017, 245, pp. 1352

   **Status: Published**

7. Chen, H., Yu, P., Hailey, D., Wang, N., Methods for assessing the quality of data in public health information systems: A critical review, Studies in Health Technology and Informatics 2014, 204, pp. 13-18.

   **Status: Published**

# List of names or abbreviations

Acquired Immune Deficiency Syndromes (AIDS)

Australian Institute of Health and Welfare (AIHW)

Chinese Center for Disease Control and Prevention (China CDC)

Chinese HIV/AIDS Comprehensive Response Information Management Systems (CRIMS)

Electronic health records (EHRs)

Human Immuno-deficiency Virus (HIV)

Information Communication Technologies (ICTs)

Information Systems (IS)

Information Technology (IT)

International Organization for Standardization (ISO)

Joint United Nations Programme on HIV/AIDS (UNAIDS)

Public Health Information Systems (PHIS)

Sustainable Development Goals (SDGs)

World Health Organization (WHO)

# Table of contents

# List of figures

# List of tables

# Chapter 1 Introduction

## 1.1 The rationale for the research

High-quality data and effective data quality assessment are vital for accurate detection and diagnosis of public health risk, for the design, implementation, and evaluation of the impact of public health interventions and for measuring public health outcomes. The World Health Organization (WHO) recommends data quality assessment should not only describe the quality status of data but also enable identification of the causes of data quality problems, thus ensuring high quality data in public health information systems (PHIS) [1, 2].

HIV (Human Immuno-Deficiency Virus)/AIDS (Acquired Immune Deficiency Syndrome) is an important public health challenge [3-5] and needs high quality data and effective data quality assessment to help end the epidemic by 2030, a target set by the Joint United Nations Programme on HIV/AIDS (UNAIDS) [6]. The Chinese HIV/AIDS Comprehensive Response Information Management System (CRIMS) is a national public health information system for HIV/AIDS prevention and control in China [7], which is currently the largest web-based HIV/AIDS surveillance system in the world [3, 8]. It has been used for nationwide HIV/AIDS data reporting and management since 2008 [3, 8].

Considering that the data-driven public health management assumes data are accurate, timely, and reliable, data quality assessment needs to be continuously and rigorously conducted to ensure high quality data in the CRIMS and PHIS. A data-driven performance assessment scheme has been established by the Chinese Centre for Disease Control and Prevention (China CDC) and implemented to assess the data quality of the CRIMS [8, 9]. Implementation of the scheme has led to improvement in quality of the reporting data in the system [9, 10]. However, certain reporting data, e.g., case demographics, case follow-up, and intervention delivery, were still inaccurate, incomplete, missing, delayed, under-reported or leaking [11-14]. Prior studies imply public health professionals lack trust in the quality of data in the CRIMS and express concerns over the quality of the data collection process [15-17]. This important concern of many public health professionals at different levels in China has been the motivation for this PhD study.

Therefore, this PhD project aims at measuring the quality of the data collection process to ensure data

quality for public health information systems. It has three research objectives: (1) review and synthesize the existing PHIS data quality assessment methods; (2) conceptualize and validate a framework to measure the quality of the PHIS data collection process; and (3) use the developed framework to evaluate the data collection process for a country-level PHIS, the CRIMS.

The project has answered the following four research questions:

- What methods and approaches are used in assessment of data quality for PHIS?
- What are the essential components of a framework to measure the quality of the public health data collection process?
- How effective is the developed framework to evaluate the quality of the data collection process for PHIS?
- What is the quality of the data collection process for the country-level PHIS, the CRIMS?

To answer the questions, this project takes two research approaches: literature review and expert elicitation. The data collection methods include systematic sampling of literature, and semi-structured interview of public health experts working in the CRIMS and a field audit at hospitals (Figure 1-1).

To ensure the research rigor of this project that might be affected by paper reviews and qualitative research methods, the quality control process and specific quality control measures were used. On literature review, the systematic literature scoping method and application of existing review tools such as the Critical Appraisal Skills Program (CASP) tools were used to assess the reliability and validity of each selected study [18, 19]. On qualitative aspects, three broad categories of validity for qualitative research in information systems proposed by Venkatesh [20] were followed. These included design validity, analytical validity, and inferential validity. Design validity is manifested by the application of a stratified sampling method in expert elicitation to identify participants for representativeness [21]. Analytical validity is demonstrated by the consistent application of a five-stage qualitative healthcare data analytic framework suggested by Pope et al for code extraction and theme emergence [22]. Inferential validity is shown using these quality control measures in the relevant sections of Chapters 2, 3, 4, and 5.

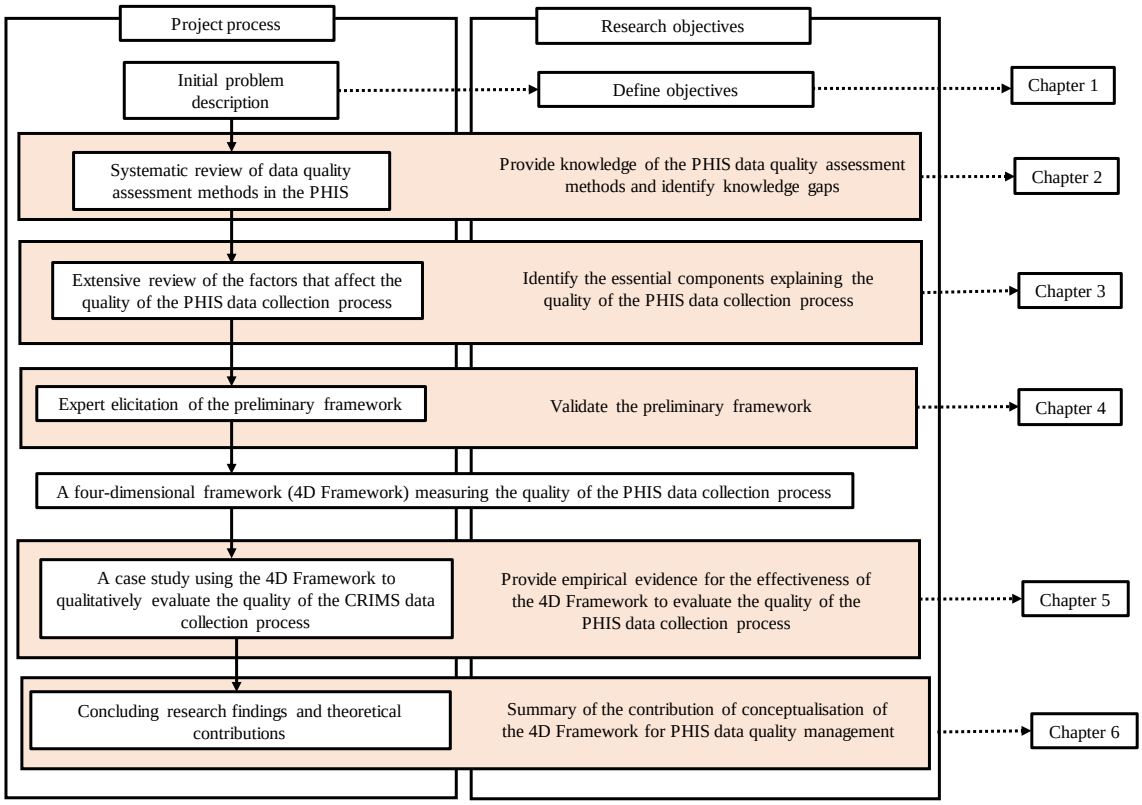


Figure 1-1 Synopsis of the methodology in this study

## 1.2 The organization of the thesis

This thesis is submitted in the format of thesis by compilation. It consists of six chapters with logic connections and research objectives illustrated in Figure 1-2.

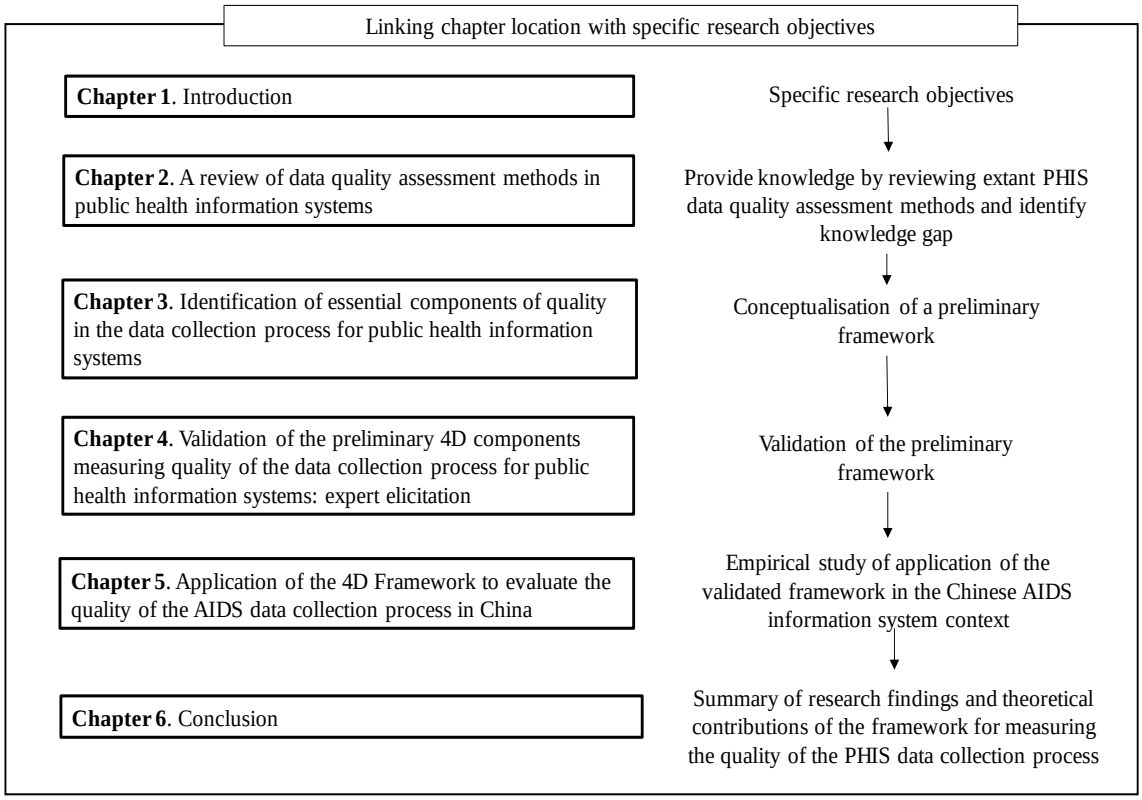


Figure 1-2 Organization of the thesis

Chapter 1 provides background information for this study. It describes the main intention of this research by highlighting the research aims and objectives. The chapter provides the organization of the thesis and a brief description of the research for each chapter. Chapters 2 to 5 provide the publications related to the research objectives (Table 1-1). These chapters start with a 'Foreword' that briefly describes the rationale for establishing the research topic and its publication venue. This is followed by the content of the article. Chapter 6 summarises the PhD research and outlines the contribution to the public health data quality assessment methods and approach for assessing the quality of the PHIS data collection process. The thesis concludes by acknowledging research limitations and pointing to further research directions. The following sections provides a brief overview of the major content of Chapters 2 to 5, the four chapters that have been published or are currently under-review by certain academic peer-reviewed journals.

Table 1-1 Publications associated with this thesis

| Paper Title | Year | Authors | Outlet | Status | Relation to Thesis |
|---|---|---|---|---|---|
| A review of data quality assessment methods for public health information systems | 2014 | Chen, H., Hailey, D., Wang, N., Yu, P.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | International Journal of Environmental Research and Public Health, 2014;11(5): 5170-5207; doi:10.3390/ijerph110505170 | Published | Chapter 2 with reprint |
| Identification of the essential components of quality in the data collection process for public health information systems | 2019 | Chen, H., Yu, P., Hailey, D., Cui, T.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | Health Informatics Journal, 2020;26(1): 664-682. doi:10.1177/1460458219848622 | Published | Chapter 3 with reprint |
| Validation of 4D components for measuring quality of the public health data collection process: expert elicitation | 2021 | Chen, H., Yu, P., Hailey, D., Cui, T.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | Journal of Medical Internet Research, 2021;23(4): e17240. doi:10.2196/17240. | Published | Chapter 4 with reprint |
| Application of a four-dimensional framework to evaluate the quality of AIDS data collection process in China | 2020 | Chen, H., Yu, P., Hailey, D., Cui, T.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | International Journal of Medical Informatics, 2021;145. PMID: S1386505620303701. doi:10.1016/j.ijmedinf.2020.104306. | Published | Chapter 5 with reprint |
| Data quality of the Chinese National AIDS information system: A critical review | 2017 | Chen, H., Yu, P., Hailey, D., Cui, T.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | Studies in Health Technology and Informatics 2017, 245, pp. 1352; PMID:29295431 | Published | Cited without reprint |
| Do we have the reliable data? An exploration of data quality for AIDS information system in China | 2013 | Chen, H., Yu, P., Wang, N.<br><br>*Percentage of contribution by the author: 78% (Including: data collection, data analysis, drafting) | Studies in Health Technology and Informatics, 2013; 192(1-2), pp. 1042; www.ncbi.nlm.nih.gov/pubmed/23920816 | Published | Cited without reprint |
| Methods for assessing the quality of data in public health information systems: A critical review | 2014 | Chen, H., Yu, P., Hailey, D., Wang, N.<br><br>*Percentage of contribution by the author: 68% (Including: data collection, data analysis, drafting) | Studies in Health Technology and Informatics, 2014; 204, pp. 13-18; doi: 10.3233/978-1-61499-427-5-13 | Published | Cited without reprint |

### 1.2.1 Chapter 2. Data quality and data quality assessment in public health

Chapter 2 focuses on the topic of data quality and data quality assessment in public health. The chapter introduces a review of extant PHIS data quality assessment methods. The review aims to investigate and compare the methods for PHIS data quality assessment to identify possible patterns and trends emerging over the first decade of the 21st century. It has addressed the first of the four research questions: "What methods and approaches are used in assessment of data quality for PHIS?"

This chapter starts by describing the concept and rationale of data quality and data quality assessment in PHIS. Public health is a data-intensive domain [23, 24] and needs high quality data for better decision-making and better population health [25]. This is routinely achieved by data quality assessment, which aims to accurately evaluate the impact of public health interventions and measure public health outcomes. Today, data quality assessment has been integrated into public health practice to ensure data quality [26, 27]. However, the problems with PHIS data quality have remained. Researchers found incomplete data collection processes and poor-quality documentations in PHIS [18, 19]. Data errors have caused inaccurate hospital performance measurement, inappropriate allocation of health funding, and failure in public health surveillance [18-22]. Studies in China, the United Kingdom and Pakistan have identified data users' lack of trust in the quality of HIV/AIDS, cancer, and health management information systems because of unreliable or uncertain data [20-22]. As there is a lack of systematic review of data quality assessment methods for PHIS, understanding the current development in methods and approaches for data quality assessment is essential for research and practice in public health informatics.

To guide the systematic review, it is necessary to identify and conceptualize a framework for evaluation of the PHIS data quality assessment methods. This is also the first research objective to be addressed in this PhD project.

Data quality is generally recognized as a multi-dimensional concept across public health and other sectors [28-30]. Data flow in a public health practice lifecycle through three phases: data, data collection process and use of data [28, 29]. From an "information chain" perspective, Karr et al propose "three hyper-dimensions" (i.e., process, data and user) to group a set of conceptual dimensions of data quality [30]. Their typology provides a comprehensive perspective for classifying data quality assessment methods which must be useful to assess all the three dimensions [30]. Thus, this review adopts the approach of Karr et al and formulates a three-dimensional (3D) conceptual framework, including the quality of the data, data use and data collection process, for appraisal of the data quality assessment methods in public health practice.

Following the proposed 3D conceptual framework, a qualitative systematic review approach was used for evaluation of the extant PHIS data quality assessment methods. This includes 32 peer-reviewed individual research publications and seven well-known institutional websites, such as the WHO and the United States CDC.

Four themes emerged from the review. The first theme is that there were differences between the institutional and the individual research publications in their approach to data quality assessment, in terms

of aims, context and scope. Compared with individual researchers, the institutions were more concerned about the effectiveness of the PHIS. They paid attention not only to the disease-specific public health contexts such as maternal health, children's health, and HIV/AIDS, but also to the routine PHIS. All levels of data management instead of a single level of analysis were under the scrutiny of the institutions.

The second theme is that coverage of the three dimensions of data quality was not equal. The dimension of data was more frequently assessed (reported in 35 publications) than data use (explicitly reported in five studies) and the data collection process (only explicitly reported in one study).

The third theme emerges as the result of the second theme, a lack of attributes and measurement indicators for data use and the data collection process. Most definitions of data quality attributes and measures referred to the data dimension as opposed to the other two dimensions. For example, completeness, accuracy, and timeliness are the attributes of the quality of data. They were the three most-used attributes frequently referring data quality attributes and measures in data quality assessment.

The last theme is that methods of assessment can be qualitative or quantitative assessment methods. The major quantitative methods were descriptive surveys and data audits, whereas the common qualitative assessment methods were interview and documentation review. Both subjective and objective strategies are useful for data quality assessment. However, only a small minority of the reviewed studies used both types of assessment. Meanwhile, field verification of the quality of data is not yet a routine practice in data quality assessment. Only five studies conducted field observations for data or for the data collection process and they were usually informal. The reliability and validity of the study was rarely reported. This theme indicated there is a need for systematic procedures that use mixed methods to assess data from multiple sources.

To sum up, this review has conceptualized a framework for evaluation of PHIS data quality assessment methods and systematically evaluated extant assessment methods for each of the three dimensions of data quality: data, data collection process and data use. The dimension of data was the focus in many data quality assessment initiatives. Inattentiveness to data use and data collection process, especially the latter might have led to persistent data quality problems in public health practice, and worse still, a lack of trust in public health data from practitioners and governments. As data quality needs to be positioned at the forefront of public health as a distinct area that deserves specific scientific research and management investment, the importance of systematic, scientific data quality assessment needs to be highlighted. All three dimensions of data quality, i.e., data, data use and the data collection process, need to be systematically evaluated. Subjective assessments of data end users' or customers' perspectives should be an indispensable component in data quality assessment for PHIS.

This research has obtained the first research objective: identification and conceptualization of a framework for evaluation of PHIS data quality assessment methods. The findings have paved the way to a specific focus on conceptualization of a framework for explaining the quality of the PHIS data collection process in this PhD project.

### 1.2.2 Chapter 3. Essential components of the quality of the data collection process in public health information systems

Chapter 3 focuses on identification of the essential components of the quality of the data collection process in PHIS. An extensive literature review was conducted, aiming to synthesizing and identifying essential components of the quality of the data collection process in PHIS. This review is a critical survey of the major findings of public health researchers and practitioners on the factors that influence the quality of the PHIS data collection process. The research has addressed the second of the four research questions: "What are the essential components that affect the quality of the public health data collection process?"

The review in this chapter starts with understanding the importance of the quality of the data collection process in PHIS, an essential element of data quality. The data collection process includes the generation, assembly, description, and maintenance of data, all of which should be of high quality [30, 31]. To date, while data quality problems originating from the process of data collection have been frequently found, the assessment of the quality of the data collection process in PHIS has not been well considered nor routinely conducted [31-33]. The quality improvement effort has been focused on assessment of the quality of data which have already been captured and stored [29, 31, 34]. As a result, the WHO reinforces that data quality assessment should not only describe the quality status of data but also enable identification of the causes of data quality problems [1, 2].

The reason for the lack of attention to the quality of the data collection process could be an insufficient clarification of the essential components for data collection. Prior review of PHIS data quality assessment (chapter 2) showed only 5% (2/39) studies specified an explicit definition of the quality of data collection [31]. A variety of quality criteria for data collection were introduced such as data accuracy, data integrity, minimum response burden for data-provider practices, and the relevance, simplicity, and layout of the data collection tools [29, 32, 35, 36]. These criteria, not taking a comprehensive picture of the entire process, were centred either around some data collection procedures, such as data recording and storage, or on quality control mechanisms [31].

Data collection is a systematic data gathering process [35], which includes a set of interrelated or interacting activities contributing to the process of transforming inputs into outputs [37]. Organizational, technical, and behavioural factors can affect the performance of the data collection process for PHIS [32, 33, 38-41]. They may "take the form of defects in organizational procedures, faulty logic, and reasoning, or human error that result in compromised performance" [42]. An operational definition or measurement for these factors has yet to be reached. At the technical level, the design of electronic data collection forms and integration of different information systems are important mechanisms. But technology advancement alone cannot always lead to high-quality data [32, 33, 41, 42]. At the individual behavioural level, a data collector's motivation and competence to perform a task, though often scrutinized through the lens of data users, have not been clarified in the context of the data collection process [41]. The unsystematic knowledge about the key factors influencing the quality of the data collection process could impair the effectiveness and efficiency of data-driven monitoring and performance evaluation mechanisms for public health programs [32, 33, 42, 43]. A recent evaluation of data quality in country health information systems by the WHO in a global

context has found that data management was the weakest component of system performance [32]. Effective process assessment of data collection that focuses on how data are collected will help standardize the performance of public health programs by comparing "the specific actions taken, events occurring, and human interactions with accepted standards" [44]. Therefore, identification of the essential components of the quality of data collection is needed to guide efforts in the development of a quality framework for PHIS. This is also the second research objective to be addressed.

The research in Chapter 3 adopts an interpretive approach for synthesis and appraisal of the factors that affect the quality of the data collection process. A five-stage health care qualitative data analytic framework suggested by Pope et al [57] was used to critically survey the factors. The reviewed components were reported in peer-refereed empirical studies or on well-known institutions' websites. The results of content analysis allow the researcher to develop categories of factors that facilitate or inhibit the quality of the PHIS data collection process. Following Pope et al approach, a preliminary four-dimensional (4D) component framework is constructed, containing four essential components, 12 subcomponents, and 149 items with either positive or negative impacts on the quality of the data collection process.

The first essential component is data collection management. It is the most reported quality component for the data collection process and half of the items belong to this component. From an organizational perspective, data collection management is an administrative process by which data are acquired, validated, stored, protected, and processed [32, 33]. The ultimate goal of data collection management is to fulfil every requirement from data users [33, 36]. Therefore, effective management requires the application of knowledge, skills, tools, and techniques to data collection activities, and the provision of enough supervision in personal and systematic process audits. Its indicators comprise appropriate data collection methods, data entry forms, and ongoing quality assurance. Therefore, the dimension of data collection management includes two subcomponents: the data collection system and quality assurance.

The second essential component is the data collector. Data collectors collect or supply data for the PHIS with whom data users should build up and nurture a relationship. At the individual level, data collectors need to have a right attitude, and adequate skills and competence for the job. They need to maintain adequate communication with each other. For them to execute their tasks adequately, their organization needs to provide adequate staffing with the right skill mix. While data collectors play an important role in the quality of the data collection process, extant data quality assessment instruments have not paid enough attention to data collectors except for their training experience. Therefore, the dimension of data collector includes four subcomponents: staffing patterns, skills and competence, communication, and attitudes towards data collection.

The third essential component is the information system. An information system (IS) is a combination of hardware, software, infrastructure, and trained personnel [29]. It requires different systems and elements to be integrated to assist data capture, data entry and data logging. Thus, continuous and systemic functionality and technical support is needed. Information systems in PHIS are characterized with automatic functions and technology support provided to the users of the system, integration of different data collection systems, and devices for data collection. They can be used to assess the IS quality.

The fourth essential component is the data collection environment. It refers to the context for data collection. In a government context, the PHIS is directly responsible to legislative, regulatory, and policy directives. Training, leadership, and funding support are the three main factors of the data collection environment.

To sum up, this research has established a preliminary framework, the 4D components that measure the quality of the PHIS data collection process. The research has obtained the first half of the second research objective, that is, conceptualization of a framework for measuring the quality of the PHIS data collection process. To validate the identified components that were distilled from qualitative analysis of the published literature, future empirical testing and practical implementation are needed.

### 1.2.3 Chapter 4. Qualitative validation of a 4D framework to measure quality of the public health data collection process

Chapter 4 focuses on validation of the preliminary framework, a 4D framework for measuring the quality of the PHIS data collection process (Chapter 3). The validation study follows an expert elicitation research approach. In a national PHIS context, the CRIMS, it has achieved the second half of the second research objective: validation of a framework for measuring the quality of the PHIS data collection process.

The research starts with reflection of the original 4D components of the quality of the PHIS data collection process and assessment of the appropriateness of the definition of the components for the validation study. For the data collection management dimension, its concepts were adopted except that the subcomponent *data collection system* was renamed *data collection protocol* to specifically refer to the guideline, plan, or handbook for data collection. For the data collector dimension, its concepts were adopted except that the component *data collector* was renamed *data collection personnel*. For the information system dimension, its concepts were adopted except that the component *information system* was renamed *data collection system* to enable the establishment of the acronym '4D' for the framework. The combined subcomponent *functions and technical support* was separated to acknowledge the different material world represented by these two concepts. For the data collection environment dimension, its concepts were all adopted.

The research approach for validation, expert elicitation, is commonly used to identify and address an uncertain subject, particularly in situations when relevant local evidence or information is incomplete [45]. The knowledge synthesized from the expert opinions forms the foundation of further research. This approach has been widely used in public health for policy decisions and generating evidence [17, 46].

The research processes include the development of an interview guide and data collection form, data collection, and data analysis. Twenty-eight Chinese HIV/AIDS data management experts, including three public health administrators, fifteen public health workers, and ten healthcare practitioners participated in the elicitation session. They represented all administrative levels in all types of organizations in the CRIMS. Qualitative data analysis was conducted according to the framework analysis approach suggested by Pope et al [22].

The 28 public health data management experts represent all levels and spectrums of personnel engaging

with the CRIMS. They had varied work experience and roles within their organizations who provided accurate and comprehensive inputs to issues related to quality of the data collection process. They agreed with the four main components derived from the literature. They ranked and commented on the importance of the original subcomponents based on their experience with the CRIMS data collection process. A total of 302 codes identified from the interview transcripts supported 75.2% (112/149) of the original indicators of the preliminary 4D component framework and generated 46 new indicators. After iterative and recursive coding, mapping, merging, deleting and classification, 116 indicators, including 82 facilitators and 34 barriers, were constructed, and put in appropriate subcomponents for measuring quality of data collection. This validated the preliminary 4D component framework.

The first component, data collection management, includes data collection protocol and quality assurance, which is measured by 41 (35.3% of the 116) indicators. The second component, the data collection environment, is measured by 37 (31.9%) indicators. These comprise leadership, training, and funding, as well as three newly added subcomponents, i.e., organizational policy, high-level management support, and collaboration among parallel organizations. The third component, data collection personnel, is described by a perception of data collection, skill and competence, communication, and staffing pattern. This is measured by 22 (19.0%) indicators. The fourth, data collection system, containing functions, integration of different data collection systems, technical support, and device for data collection, is measured by 16 (13.8%) indicators.

The component of data collection management includes two essential subcomponents *data collection protocol* and *quality assurance*. A total of 41 indicators, including 28 facilitators and 13 barriers, were finalized for measuring data collection management (Appendix B). Under data collection management, the methods and protocols should be well developed, uniform and implemented by data collection personnel. Management of quality assurance needs to define the criteria of quality assurance, maintain the consistency of quality assurance, and ensure the implementation and conduct of quality assurance. Issues of concern include the sources and location of data, use and viability of audits, and communication between data collection staff, particularly those at local levels, and their superiors.

The data collection environment includes three original subcomponents (leadership, training, funding), and three newly added ones (organizational policy, high-level management support, and collaboration among parallel organizations). There are 37 indicators including 27 facilitators and 10 barriers for measuring the data collection environment (Appendix B). A friendly data collection environment is an important factor for a high-quality public health data collection process. Leadership and training are considered as the two most important items in the list of subcomponents for this component. Leadership also emerged as a decisive factor. This is consistent with the recommendation by the International Organization for Standardization (ISO) that top management should "demonstrate leadership and commitment with respect to the quality management system" [37]. In addition, three newly emerging subcomponents, i.e., organizational policy, high-level management support, and collaboration among parallel organizations, emphasize avoidance of data collection unduly intruding on health facilities' operation, and adequacy of communication between different organizations. From an expert perspective, if the level of support from

the data collection environment is inadequate, or not suitably administered, quality will deteriorate.

Data collection personnel includes four essential subcomponents as the following: perception of data collection, skills and competence, communication, and staffing pattern. There are 22 indicators including 17 facilitators and five barriers for measuring data collection personnel (Appendix B). On data collection personnel, all practitioners agreed on the importance of work attitude, competence, and data audit skills. There appeared to be some variation in opinion on the difficulty of the data collection process. The priority placed by the management in a hospital could significantly affect performance. "Burnout" exhibited by staff might appear after long-term work in data collection and would require remediation. Skills and work competence were considered as a "must-have" capability for frontline data collectors. Increasing the number of competent staff would in principle help to improve the data collection quality.

The data collection system, the fourth component, includes four subcomponents: functions of the system, integration of different information systems, technical support, and devices for data collection. There are 16 indicators including 10 facilitators and 6 barriers developed for measuring the component data collection system (Appendix B). The quality of the data collection system will be influenced by the continuing changes in the performance and availability of information communication technologies (ICTs). Functions in the system should facilitate the visualization of routinely collected data. The system should be humane for those who operate it, convenient and error-free for data collection.

To sum up, the research empirically supported the 4D component framework that derived from the inductive analysis of the international literature (Chapter 3). Data collection management, data collection environment, data collection personnel, and data collection system are the key components that affect the quality of the public health data collection process. The research has answered the third research question: "How effective is the developed framework to evaluate the quality of the data collection process for PHIS?"

Also, the findings suggested Chinese HIV/AIDS information management practice provided an effective validation case and enriched the study of the quality of the PHIS data collection process. For ethical conduct of research to benefit the study participants, the confirmed 4D component framework was further used for root cause analysis to investigate and identify the "real" factors behind declining data quality [15, 16], the quality of the CRIMS data collection process (Chapter 5).

### 1.2.4 Chapter 5. Quality of the Chinese HIV/AIDS data collection process

Chapter 5 presents a case study evaluating the quality of the CRIMS data collection process by using the developed 4D framework. It aims to address the fourth research question: "What is the quality of the data collection process for the CRIMS?"

Chapter 5 starts with introduction of the CRIMS. The HIV/AIDS epidemic remains an important public health challenge in China [3-5]. By October 2019, approximately 958,000 persons living with HIV/AIDS (PLWHA) were recorded. The predicted number of PLWHA by the end of 2018 was between 1.1 and 1.4 million [4, 47]. As the CRIMS is a national data repository for the HIV/AIDS "project planning, budgeting, implementation, monitoring and evaluation" [7], the CRIMS data collection process needs to be of high

quality. In the last decade, a data-driven performance assessment scheme has been established to assess the data quality of the CRIMS [8, 9]. Implementation of the scheme has led to improvement in quality of the reporting data in the system [9, 10]. However, 61% (37/61) of data quality assessment studies reported quality of data (i.e., data representativeness, completeness, accuracy) without identification of the causes of quality problems [10]. Because the 4D framework provides a multi-dimensional lens on the quality of the PHIS data collection process, this research aims to apply the framework to the CRIMS to identify gaps in the process and suggest improvement strategies for HIV/AIDS data collection in China.

The research was carried out in China from September 2014 to April 2015. The research data were collected through semi-structured interviews with the participants and from field observations in hospital. Stratified convenience sampling was conducted to recruit public health professionals in 19 organizations which represented all levels of the CRIMS. Public health practitioners involved in HIV/AIDS data management were asked the following question: "What are the factors and how do they affect the quality of the data collection process in the CRIMS?" All the interviews were transcribed verbatim. Transcripts were sent to the interviewees for validation before being used in data analysis. Data were open coded, reviewed and grouped into the indicator statements in the framework. Iterative analysis and comparison of the narratives with the indicator statements in the 4D framework was conducted to achieve theoretical saturation. Guided by the 4D framework, the suggested facilitative factors were used as improvement strategies to fill in the gaps for quality improvement.

As a result, 75 (65%) indicator statements in the 4D Framework were identified in this research. Of these, 50 were facilitators (accounting for 61% of the 82 facilitators) and 25 were barriers (74% of the 34 barriers). The proportion of facilitators observed for Data Collection Environment was low at 37% (10/27). With the other components the proportions identified were 68% (19/28) for Data Collection Management, 94% (12/17) for Data Collection Personnel and 90% (9/10) for Data Collection System. The proportion of barriers observed was low for Data Collection Management (7/13, 54%), and high for Data Collection Environment (9/10, 90%), Data Collection Personnel (4/5, 80%) and Data Collection System (5/6, 83%).

The perceived major gaps in the CRIMS mapping with the 4D framework included (1) an impractical data collection protocol and invalid data quality assessment mechanism for data collection management; (2) weak leadership and unsupportive organizational policy for data collection environment; (3) poor communication and job fatigue for data collection personnel; and (4) inflexibility and inaccessibility of the data collection system for the clinical end-users.

The research notes that Data Collection Environment had a much lower proportion of facilitators than the other three dimensions, and a high proportion of barriers. This suggests the Data Collection Environment is an immediate focal area for improvement. Although Data Collection Management attracted some adverse comments from the study participants it had a much lower proportion of barriers than the other dimensions and a high proportion of facilitators, suggesting reasonable levels of performance. Weak leadership and unsupportive organizational policy were the major complaints from frontline workers in the dimension of data collection environment. Barriers to the performance of the data collection personnel include job fatigue and inaccessibility to the CRIMS data. The research suggests these gaps cannot be completely overcome

by the data collection personnel themselves. Meanwhile, the inflexible CRIMS data collection system and its separation from the local electronic health records (EHRs) in hospitals have impaired the utility and usage of the HIV/AIDS data for clinical end-users. There is a need to address the uniformity and standardization of the EHR data to support public health.

Improvement strategies suggested by the interviewees to fill the gaps included (1) engagement of frontline public health professionals in the design of the data collection protocol, and standardizing quality assurance procedures; (2) strengthening leadership, high-level management, on-going training and technical support; (3) enhancement of recognition and reward of data collector's contribution and efforts; and (4) meeting clinical end-users' needs for integrated data collection systems.

To sum up, the research evaluates the quality of the CRIMS data collection process and analyses and synthesizes the data collection management problems across all levels of organizations involved in this process. The findings show the CRIMS has achieved better-quality data collection management. The research has identified the process gaps and mapped these to the indicator statements in the 4D framework. It has also provided strategies to address these gaps. The findings support a multi-dimensional approach to improve performance of the PHIS data collection process by the top level of the country's health system instead of by individual health facilities. The research demonstrates the 4D framework can be used as a diagnostic tool for decision makers on data collection process improvement for public health information systems.

# Chapter 2 A review of data quality assessment methods for public health information systems

## Foreword

The previous chapter introduced the rationale for this PhD project, including the research aims and questions, and how these are addressed through the ensuing chapters. Responding to Objective 1 of the project, i.e., review and synthesis of the existent PHIS data quality assessment methods, this chapter presents a systematic review. In this chapter Karr's conceptual framework of data quality is brought to conceptualize the PHIS data quality from three dimensions: data, data use and data collection process [30]. Based on the Karr's approach, a three-dimensional conceptual framework is proposed for data quality assessment in public health practice. The latter half of the chapter follows the conceptual framework and systematically reviews the extant PHIS data quality assessment methods. This lays the groundwork for the introduction of the identification of the essential components of and thus conceptualisation of a framework to measure the quality of the PHIS data collection process. In reference to Karr's use of the term 'dimension' to unpack the concept of data quality into three components, this thesis uses 'dimension' to label the components of the 3D framework for data quality and the 4D framework for the quality of the data collection process.

This chapter is a reproduction with minor corrections of the published full paper: Hong Chen, David Hailey, Ning Wang, and Ping Yu (2014) A review of data quality assessment methods for public health information systems. *International Journal of Environmental Research and Public Health*, 2014, 11(5), pp. 5170-5207 doi:10.3390/ijerph110505170.

The Table and Figure numbers, the Reference numbers and the Section numbers have been adjusted to fit within the structure of the thesis. The appendixes are included as Appendix Table A1, A2, and A3 in this thesis.

## Abstract

High quality data and effective data quality assessment are required for accurately evaluating the impact of public health interventions and measuring public health outcomes. Data, data use, and data collection process, as the three dimensions of data quality, all need to be assessed for overall data quality assessment. We reviewed current data quality assessment methods. The relevant study was identified in major databases and well-known institutional websites. We found the dimension of data was most frequently assessed. Completeness, accuracy, and timeliness were the three most-used attributes among a total of 49 attributes of data quality. The major quantitative assessment methods were descriptive surveys and data audits, whereas the common qualitative assessment methods were interview and documentation review. The limitations of the reviewed studies included inattentiveness to data use and data collection process, inconsistency in the definition of attributes of data quality, failure to address data users' concerns and a lack of systematic procedures in data quality assessment. This review study is limited by the coverage of the databases and the breadth of public health information systems. Further research could develop consistent data quality definitions and attributes. More research efforts should be given to assess the quality of data use and the quality of data collection process.

Keywords: data quality; information quality; data use; data collection process; evaluation; assessment; public health; population health; information systems

## 2.1 Introduction

Public health is "the science and art of preventing disease, prolonging life, and promoting physical health and efficiency through organized community efforts" [48]. The ultimate goal of public health is to improve health at the population level, and this is achieved through the collective mechanisms and actions of public health authorities within the government context [48, 49]. Three functions of public health agencies have been defined: assessment of health status and health needs, policy development to serve the public interest, and assurance that necessary services are provided [23, 49]. Because data, information and knowledge underpin these three functions, public health is inherently a data-intensive domain [23, 24]. High quality data are the prerequisite for better information, better decision-making and better population health [25].

Public health data represent and reflect the health and wellbeing of the population, the determinants of health, public health interventions and system resources [50]. The data on health and wellbeing comprise measures of mortality, ill health, and disability. The levels and distribution of the determinants of health are measured in terms of biomedical, behavioural, socioeconomic and environmental risk factors. Data on public health interventions include prevention and health promotion activities, while those on system resources encompass material, funding, workforce, and other information [50].

Public health data are used to monitor trends in the health and wellbeing of the community and of health determinants. Also, they are used to assess the risks of adverse health effects associated with certain determinants, and the positive effects associated with protective factors. The data inform the development of public health policy and the establishment of priorities for investment in interventions aimed at

modifying health determinants. They are also used to monitor and evaluate the implementation, cost and outcomes of public health interventions, and to implement surveillance of emerging health issues [50].

Thus, public health data can help public health agencies to make appropriate decisions, take effective and efficient action, and evaluate the outcomes [51, 52]. For example, health indicators set up the goals for the relevant government-funded public health agencies [25]. Well-known health indicators are the Millennium Development Goals (MDGs) 2015 for the United Nations member states [53]; the European Core Health Indicators for member countries of the European Union [54]; "Healthy People" in the United States, which set up 10-year national objectives for improving the health of US citizens [55]; "Australia: The Healthiest Country by 2020" that battles lifestyle risk factors for chronic disease [56]; and "Healthy China 2020", an important health strategy to improve the public's health in China [57].

Public health data are generated from public health practice, with data sources being population-based and institution-based [25, 50]. Population-based data are collected through censuses, civil registrations, and population surveys. Institution-based data are obtained from individual health records and administrative records of health institutions [25]. The data stored in public health information systems (PHIS) must first undergo collection, storage, processing, and compilation. The procured data can then be retrieved, analysed, and disseminated. Finally, the data will be used for decision-making to guide public health practice [25]. Therefore, the data flows in a public health practice lifecycle consist of three phases: data, data collection process and use of data.

PHIS, whether paper-based or electronic, are the repositories of public health data. The systematic application of information and communication technologies (ICTs) to public health has seen the proliferation of computerized PHIS around the world [58-60]. These distributed systems collect coordinated, timely, and useful multi-source data, such as those collected by nation-wide PHIS from health and other sectors [61]. These systems are usually population-based, and recognized by government-owned public health agencies [62].

The computerized PHIS are developed with broad objectives, such as to provide alerts and early warning, support public health management, stimulate research, and to assist health status and trend analysis [26]. Significant advantages of PHIS are their capability of electronic data collection, as well as the transmission and interchange of data, to promote public health agencies' timely access to information [59, 63]. The automated mechanisms of numeric checks and alerts can improve validity and reliability of the data collected. These functions contribute to data management, thereby leading to the improvement in data quality [64, 65].

Negative effects of poor data quality, however, have often been reported. For example, Australian researchers reported coding errors due to poor quality documentations in the clinical information systems. These errors had consequently led to inaccurate hospital performance measurement, inappropriate allocation of health funding, and failure in public health surveillance [66].

The establishment of information systems driven by the needs of single-disease programs may cause excessive data demand and fragmented PHIS systems, which undermine data quality [25, 27]. Studies in

China, the United Kingdom and Pakistan reported data users' lack of trust in the quality of AIDS, cancer, and health management information systems due to unreliable or uncertain data [67-69].

Sound and reliable data quality assessment is thus vital to obtain the high data quality which enhances users' confidence in public health authorities and their performance [26, 27]. As countries monitor and evaluate the performance and progress of established public health indicators, the need for data quality assessment in PHIS that store the performance-and-progress-related data has never been greater [27, 70, 71]. Nowadays, data quality assessment that has been recommended for ensuring the quality of data in PHIS becomes widespread acceptance in routine public health practice [26].

Data quality in public health has different definitions from different perspectives. These include: "fit for use in the context of data users" [29, p2]; "timely and reliable data essential for public health core functions at all levels of government" [72, p114], and "accurate, reliable, valid, and trusted data in integrated public health informatics networks" [73]. Whether the specific data quality requirements are met is usually measured along a certain number of data quality dimensions. A dimension of data quality represents or reflects an aspect or construct of data quality [74].

Data quality is recognized as a multi-dimensional concept across public health and other sectors [28-30]. Following the "information chain" perspective, Karr et al. used "three hyper-dimensions" (i.e., process, data and user) to group a set of conceptual dimensions of data quality [30]. Accordingly, the methods for assessment of data quality must be useful to assess these three dimensions [30]. We adopted the approach of Karr et al. because their typology provided a comprehensive perspective for classifying data quality assessment. However, we replace "process" by "data collection process" and "user" by "data use". "Process" is a broad term and may be considered as the whole process of data flows, including data and use of data. "User" is a specific term related to data users or consumers and may ignore the use of data. To accurately reflect the data flows in the context of public health, we define the three dimensions of data quality as data, data use and data collection process. The dimension of data focuses on data values or data schemas at record/table level or database level [30]. The dimension of data use, related to use and user, is the degree and manner in which data are used [30]. The dimension of data collection process refers to the generation, assembly, description and maintenance of data [30] before data are stored in PHIS.

Data quality assessment methods generally are based on the measurement theory [38, 75]. Each dimension of data quality consists of a set of attributes. Each attribute characterizes a specific data quality requirement, thereby offering the standard for data quality assessment [30]. Each attribute can be measured by different methods; therefore, there is flexibility in methods used to measure data quality [38, 75, 76]. As the three dimensions of data quality are embedded in the lifecycle of public health practice, we propose a conceptual framework for data quality assessment in PHIS (Figure 2-1).

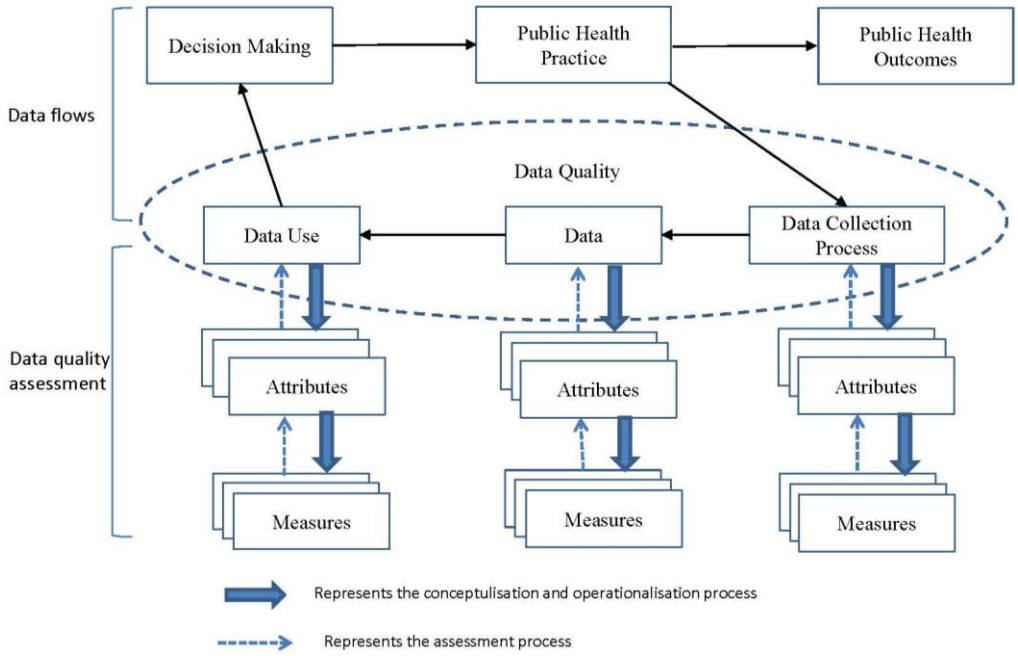


Figure 2-1 Conceptual framework of data quality assessment in public health practice

Although data quality has always been an important topic in public health, we have identified a lack of systematic review of data quality assessment methods for PHIS. This is the motivation for this study because knowledge about current developments in methods for data quality assessment is essential for research and practice in public health informatics. This study aims to investigate and compare the methods for data quality assessment of PHIS so as to identify possible patterns and trends emerging over the first decade of the 21st century. We take a qualitative systematic review approach using our proposed conceptual framework.

## 2.2 Literature review methods

### 2.2.1 Literature search

We identified publications by searching several electronic bibliographic databases. These included Scopus, IEEE Xplore, Web of Science, ScienceDirect, PubMed, Cochrane Library and ProQuest. Because many public health institutes also published guidelines, frameworks, or instruments to guide the institutional approach to assess data quality, some well-known institutions' websites were also reviewed to search for relevant literature. The following words and MeSH headings were used individually or in combination: "data quality", "information quality", "public health", "population health", "information system *", "assess *", "evaluat *". ("*" was used to find the variations of some word stems.) The articles were confined to those published in English and Chinese language.

The first author performed the literature search between June 2012 and October 2013. The inclusion criteria were peer-refereed empirical studies or institutional reports of data quality assessment in public health or PHIS during the period 2001–2013. The exclusion criteria were narrative reviews, expert opinion,

correspondence and commentaries in the topic area that lacked detailed information on research design, execution and/or data analysis. To improve coverage, a manual search of the literature was conducted to identify papers referenced by other publications, papers and well-known authors, and papers from personal databases.

### 2.2.2 Selection of publications

Citations identified in the literature search were screened by title and abstract for decisions about inclusion or exclusion in this review. If there was uncertainty about the relevance of a citation, the full text was retrieved and checked. A total of 202 publications were identified and were manually screened. If there was uncertainty about whether to include a publication, its relevance was checked by the fourth author. Finally, 39 publications that met the inclusion criteria were selected. The screening process is summarized in Figure 2-2.

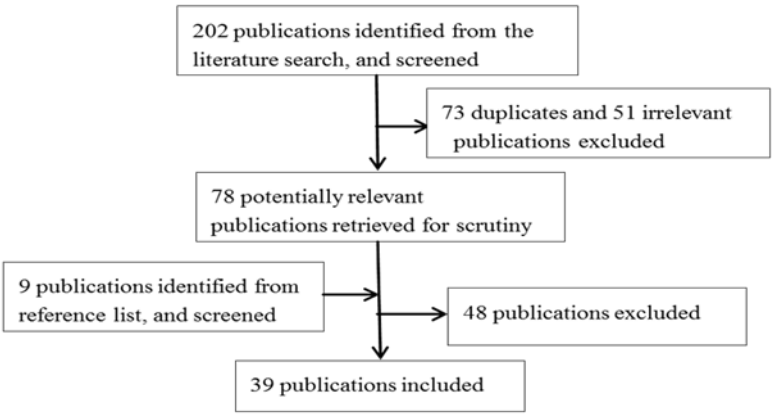

Figure 2-2 Publication search process

### 2.2.3 Data abstraction

The selected publications were stored in an EndNote library. Data extracted from the publications included author, year of publication, aim of data quality assessment, country and context of the study, function and scope of the PHIS, definition of data quality, methods for data quality assessment, study design, data collection methods, data collected, research procedure, methods for data analysis, key findings, conclusions and limitations.

The 39 publications were placed in two groups according to whether they were published by a public health institution at national or international level or by individual researchers. If the article was published by the former, it is referred to as an institutional publication, if by the latter, as a research paper.

## 2.3 Results

Of the 39 publications reviewed, 32 were peer-refereed research papers and seven were published by public health institutions. The institutional publications are listed in Table 2-1.

Table 2-1 Institutional data quality assessment publications

| Acronym | Title | Institution |
|---|---|---|
| CDC's Guidelines [59] | Updated Guidelines for Evaluating Public Health Surveillance Systems | United States Centers for Diseases Control and Prevention |
| CIHI DQF [29] | CIHI Data Quality Framework | Canadian Institute for Health Information |
| ME DQA [28, 77] * | Data Quality Audit Tool | MEASURE Evaluation Project |
| ME PRISM [41, 78] | Performance of Routine Information System Management Version 3.1 | MEASURE Evaluation Project |
| WHO DQA [79, 80] | The Immunization Data Quality Audit (DQA)Procedure; Immunization Data Quality Self-assessment (WHO DQS) Tool | Department of Immunization Vaccines and Biologicals, World Health Organization |
| WHO DQRC [81] | Guide to the Health Facility Data Quality Report Card | World Health Organization |
| WHO HMN [82] | Assessing the National Health Information System An Assessment Tool Version 4.00 | Health Metrics Network, World Health Organization |

Note. * ME DQA is adopted by the Global Fund to Fight AIDS, Tuberculosis and Malaria.

27 of the 39 reviewed publications were published between 2008 and 2013. There was a trend of increasing numbers of research papers per year, suggesting an increasing research focus on data quality with the wider adoption of computerised PHIS in recent years.

The results are organized as follows. First, the aims of the studies are given. This is followed by context and scope identified in Section 3.2. Section 3.3 examines the methods for data quality assessment. A detailed summary of the findings concludes the results in Section 3.4. For each section, a comparison between institutional publications and research papers was conducted, where this was possible and meaningful.

### 2.3.1 Aims of the reviewed studies

The main aims of the studies are assessing the quality of data (19 publications [28, 29, 79, 81, 83-97]) and assessing the performance of the PHIS (17 publications [59, 65, 78, 79, 82, 83, 95, 98-107]). Five studies assessed data use and explored the factors influencing data use [68, 69, 89, 108, 109]. Four studies investigated the facilitators and barriers for achieving high quality data and systems [65, 78, 96, 103]. Three studies compared or developed methods for the improvement of data quality assessment or data exchange [91, 93, 110]. Finally, two studies assessed data flow [29, 108].

The institutions tended to focus on the PHIS system and the data [28, 29, 59, 78, 79, 81, 82]. Data use, comparison of different PHIS, identification of the factors related to poor data quality, and analysis of data flow were also reported in research papers [65, 68, 69, 89, 91, 93, 96, 99, 103, 108-111].

### 2.3.2 Context and scope of the studies

The contexts of the studies were primarily confined to the public health domain, with other settings addressed occasionally.

Two types of public health context were covered in the institutional publications. The first included specific disease and health events, such as AIDS, tuberculosis, malaria, and immunization [28, 59, 79]. The latter was the public health system. This included public health project/program data management and reporting, routine health information systems, and PHIS under a national health institute [25, 28, 41, 78, 81, 82].

Most research studies were conducted in disease-specific public health contexts. Ten were in the maternal and children's health setting, e.g., immunization, childbirth, maternal health and hand-foot-mouth disease [85, 90, 93-95, 106-108, 110, 111]. Another five were delivered in the context of HIV/AIDS prevention and care [86, 87, 101, 103, 105]. Two studies were related to tuberculosis [84, 99]. Other contexts included multi-disease surveillance system, primary health care, acute pesticide poisoning, road data or road safety, aboriginal health, monkey pox, and cancer [65, 68, 88, 89, 92, 96, 104, 112]. In addition, clinical information management was studied in 4 research papers [91, 98, 100, 109]. National health management information systems were studied in 1 publication [69].

The public health data from information systems operated by agencies other than public health were also assessed. They include the National Coronial Information System managed by the Victorian Department of Justice in Australia, women veteran mortality information maintained by the U.S. Department of Veterans' Affairs, and military disability data from U.S. Navy Physical Evaluation Board [85, 89, 102].

The studies were conducted at different levels of the PHIS, including health facilities that deliver the health service and collect data (e.g., clinics, health units, or hospitals), and district, provincial and national levels where PHIS data are aggregated and managed. The institutions took a comprehensive approach targeting all levels of PHIS [28, 29, 59, 78, 79, 81, 82]. Twenty-seven research studies were conducted at one level [65, 84-94, 96, 98, 102, 107, 110-112]. Of these, 14 were conducted at a record collection level which delivered health service and collected data (clinics, health units, or hospitals) [65, 86, 87, 93, 94, 96, 98, 110].

The other 13 studies assessed the PHIS at management level of public health authorities that manage the data. Only 4 research papers covered more than one level of the system [69, 95, 103, 105], two of which were multi-country studies [95, 105]. Lin et al. studied the surveillance system at national level, provincial level, and at surveillance sites [103].

### 2.3.3 Methods for data quality assessment

Analysis of methods for data quality assessment in the reviewed publications is presented in three sections, based on the dimensions of data quality that were covered: data, data use or data collection process. Seven perspectives were reviewed, including quality attributes for each dimension, major measurement indicators for each attribute, study design/method of assessment, data collection methods, data analysis methods,

contributions and limitations.

### 2.3.3.1 Methods for Assessment of the Dimension of Data

In this section, the concept of data quality is a narrow one, meaning the quality of the dimension of data. All of the institutional publications and 28 research papers, a total of 35 articles, conducted assessment of the quality of data [28, 29, 59, 65, 78, 79, 81, 82, 84-107, 110-112]. Matheson et al. introduced the attributes of data quality but did not give assessment methods [109]. Additional information is provided in Appendix A Table A1.

#### 2.3.3.1.1 Quality attributes of data and corresponding measures

A total of 49 attributes were used in the studies to describe data quality, indicating its multi-dimensional nature. Completeness, accuracy and timeliness were the three attributes measured most often.

Completeness was the most-used attribute of data quality in 24 studies (5 institutional and 19 research publications) [28, 59, 65, 78, 79, 81, 84, 86-88, 91, 94, 98-104, 106, 107, 110-112]. This was followed by accuracy, in 5 institutional and 16 research publications [28, 29, 59, 78, 79, 84, 86-90, 93-95, 98, 101-103, 107, 110, 112]. The third most-used attribute, timeliness, was measured in 5 institutional and 4 research publications [29, 65, 78, 79, 81, 82, 102, 107, 111].

The attributes of data quality are grouped into two types: those of good data quality and those of poor data quality (Table 2-2).

Table 2-2 Attributes of data quality

| Item | Attribute |
|---|---|
| High data quality (38) | Completeness, accuracy or positional accuracy, timeliness or up-datedness or currency, validity, periodicity, relevance, reliability, precision, integrity, confidentiality or data security, comparability, consistency or internal consistency or external consistency, concordance, granularity, repeatability, readily useableness or usability or utility, objectivity, ease with understanding, importance, reflecting actual sample, meeting data standards, use of standards, accessibility, transparency, representativeness, disaggregation, data collection method or adjustment methods or data management process or data management |
| Poor data quality (11) | Missing data, under-reporting, inconsistencies, data errors or calculation errors or errors in report forms or errors resulted from data entry, invalid data, illegible hand writing, non-standardization of vocabulary, and inappropriate fields |

Inconsistencies in the definition of attributes were identified. The same attribute was sometimes given different meanings by different researchers. One example of this was “completeness”. Some institutions required conformity to the standard process of data entry, such as filling in data elements in the reporting forms [41, 59, 78, 81]. Completeness was represented as the percentage of blank or unknown data, not zero/missing, or proportion of filling in all data elements in the facility report form [41, 59, 78, 81]. The ME PRISM, instead, defined completeness as the proportion of facilities reporting in an administrative area

[78]. The other definition of completeness was the correctness of data collection methods in ME DQA, i.e., "complete list of eligible persons or units and not just a fraction of the list" [28] .

Of the 19 research papers including completeness as an attribute, 12 measured the completeness of data elements as "no missing data or blank" [65, 84, 86-88, 94, 98, 101, 110-112]. Dixon *et al.* defined completeness as considering both filling in data elements and data collection methods [91]. Four studies measured completeness of data by the sample size and the percentage of health facilities that completed data reports [99, 103, 104, 106]. The remaining two studies did not give precise definitions [88, 102].

On the other hand, different attributes could be given the same meaning. For example, the ME DQA defined accuracy as "validity", which is one of two attributes of data quality in CDC's Guidelines [28, 59]. Makombe, et al. considered data were accurate if none of the examined variables in the site report were missing [87]. This is similar to the definition of completeness, as "no missing data" or "no blank of data elements" in the reports by other studies.

#### 2.3.3.1.2 Study design

Quantitative methods were used in all studies except that of Lowrance et al. who used only qualitative methods [101]. Retrospective, cross-sectional survey was commonly used for quantitative studies. Pereira et al. conducted a multi-centre randomized trial [110].

Qualitative methods, including review of publications and documentations, interviews with key informants, and field observations, were also used in 8 studies [28, 82, 94, 98, 99, 103, 107, 110]. The purpose of the application of qualitative methods was primarily to provide the context of the findings from the quantitative data. For example, Hahn et al. conducted a multiple-case study in Kenya to describe clinical information systems and assess the quality of data. They audited a set of selected data tracer items, such as blood group and weight, to assess data completeness and accuracy. Meanwhile, they obtained end-users' views of data quality from structured interviews with 44 staff members and qualitative in-depth interviews with 15 key informants [98].

The study subjects varied. In 22 publications, the study subjects were entirely data [59, 79, 81, 84-93, 95-97, 102, 104, 106, 111, 112], in 4 publications they were entirely users or stakeholders of the PHIS [29, 82, 100, 101]. Three publications studied both the data and users [65, 98, 110]. Study subjects in research included data and publications conducted by Dai et al. [107], data, documentations of instructions and key informants in four studies [28, 78, 94, 99], and data, user, documentations of guidelines and protocols, and data collection process by Lin et al. [103]. Both data and users as part of study subjects were reported in 8 publications [28, 65, 78, 94, 98, 99, 103, 110].

The sampling methods also varied. Only the study by Clayton et al. calculated sample size and statistical power [93]. Freestone et al. determined the sample size without explanation [89]. One study used two-stage sampling [93]. Ten studies used multi-stage sampling methods [28, 65, 79, 86, 89, 92, 93, 95, 106, 110]. The rest used convenience or purposive sampling. The response rates were reported in two studies [100, 110].

The data collection period ranged from one month to 16 years [105, 112]. The study with the shortest time frame of one month had the maximum number of data records, 7.5 million [105], whereas the longest study, from 1970 to 1986, collected only 404 cases of disease [112]. The sample size of users ranged from 10 to 100 [82, 99].

#### 2.3.3.1.3 Data collection methods

Four methods were used individually or in combination in data collection. These were: field observation, interview, structured and semi-structured questionnaire survey, and auditing the existing data. Field observation was conducted using checklist and rating scales, or informal observations on workplace walkthroughs [28, 78, 98, 103]. Open, semi-structured or structured interviews were used when the study subjects were users or stakeholders of the PHIS [29, 78, 82, 94, 98-101, 103]. Auditing was used in directly examining existing datasets in PHIS, looking for certain data elements or variables. The benchmarks used for auditing included: in-house-defined data standards, international or national gold standards, and authoritative datasets [59, 78, 79, 81, 84, 86-93, 95, 96, 102, 104-106, 110-112]. The effect of auditing was enhanced by field observations to verify the accuracy of data sets [28, 78, 79, 95, 98, 103].

#### 2.3.3.1.4 Data analysis methods

Data analysis methods were determined by the purpose of the study and the types of data collected.

For the quantitative data, descriptive statistics were often used. For example, continuous data were usually analysed by the value of percentage, particularly for the data about completeness and accuracy, to ascertain whether they reached the quality standards. This method was most often used in 24 papers [28, 65, 78, 79, 81, 84-87, 89-96, 98, 102-104, 106, 110, 111]. Plot chart, bubble scatter chart, and confidence intervals were also used in two studies [89, 106]. Other common statistical techniques included: correlation relationship, the Chi-square test, and the Mann–Whitney test [93, 95, 106]. The geographic information system technique was reported in 3 studies [88, 89, 112]. Seven studies reported the use of questionnaires or checklists with a Likert scale or a yes/no tick, as well as simple, summative and group scoring methods [28, 29, 78, 82, 95, 99, 100].

In the publications with data as the study subject, a certain number of data variables were selected, but the reason(s) for the section was (were) not always given. They included elements of demographics such as age, gender, and birth date, and specific information such as laboratory testing results, and disease code. The minimum and maximum number of data variables was 1 and 30, respectively [95, 96].

The qualitative data were transcribed first before semantic analysis by theme grouping methods [101].

### 2.3.3.2 Methods for Assessment of the Dimension of Data Use

Ten studies, including one institutional publication and nine research papers, are reviewed in this section [68, 69, 78, 82, 89, 98-100, 108, 109]. Five studies were concerned with the assessment of data use and the factors influencing data use [68, 69, 89, 108, 109]. The other five included assessment of data use, but this was not always highlighted [78, 82, 98-100]. Details are given in Appendix A Table A2.

#### 2.3.3.2.1 Quality attributes of data use and corresponding measures

A total of 11 attributes were used to define the concept of data use. These were: trend in use, use of data or use of information, system use or usefulness of the system, intention to use, user satisfaction, information dissemination or dissemination of data, extent of data source recognition and use or specific uses of data, and existence and contents of formal information strategies and routines.

The measures fall into three categories: data use for the purpose of action, planning and research; strategies and mechanisms of data use; and awareness of data sources and data use.

The first category of measures was mentioned in eight studies [68, 78, 82, 89, 98, 99, 108, 109]. For example, actioned requests from researchers, the number of summaries/reports produced, and the percentage of report use [78, 89, 109]. Freestone et al. calculated actioned requests from researchers who do not have access to the PHIS [89]. The measurement indicators in ME PRISM were report production and display of information. They were assessed by whether and how many reports containing data from the PHIS were compiled, issued, fed back and displayed for a set time frame [78]. Saeed et al. assessed the use of data by predefined criteria, including the availability of comprehensive information, whether data were used for planning and action at each level, and whether feedback was given to the lower organizational level of the public health system [99].

The second category of measures was assessed in five studies [68, 69, 82, 99, 108]. The criteria of the measurement included the availability of a feedback mechanism, policy and advocacy, the existence and the focus of formal information strategies, and routines of data use [68, 82, 108].

The third category measured users' awareness of data use which was reported in two studies [68, 100]. Petter and Fruhling applied the DeLone and McLean information systems success model [100]. They used the framework to evaluate system use, intention to use, and user satisfaction in 15 questions by considering the context of the PHIS, which was an emergency response medical information system. Wilkinson and McCarthy recommended examining whether the studied information systems were recognized by the users in order to assess the extent of data source recognition among respondents [68].

#### 2.3.3.2.2 Study design

Three studies only used quantitative methods [78, 89, 100] and three studies only used qualitative methods [69, 98, 108]. The remaining four studies combined qualitative and quantitative methods [68, 82, 99, 109]. Interviews, questionnaire surveys, reviews of documentation and abstracts of relevant data were used in the studies.

#### 2.3.3.2.3 Data collection methods

The sources of information for the study subjects included users and stakeholders, existing documents, and data from the PHIS. Study subjects were all users in six studies [68, 69, 82, 98, 100, 108], and entirely data in the study by Freestone et al. [89]. Both user and documentation were studied in two studies [78, 99], and in one study together with data [109]. Convenience or purposive sampling was generally used.

Among nine studies whose study subjects were users, structured and semi-structured questionnaire surveys,

group discussions, and in-depth interviews were used to collect data. Use of self-assessment, face-to-face communication, telephone, internet telephony, online, email, facsimile and mail were reported in the studies. For example, Wilkinson and McCarthy used a standardized semi-structured questionnaire for telephone interviews with key informants [68]. Petter and Fruhling used an online survey as well as facsimile and mail to the PHIS users [100]. Qazi and Al administered in-depth, face-to-face and semi-structured interviews with an interview guide [69]. Saeed et al. predefined each criterion for data use and measured it by a 3-point Likert scale. They assessed each criterion through interviewing key informants and consulting stakeholders. Desk review of important documents, such as national strategic plans, guidelines, manuals, annual reports and databases was also reported in their study [99].

Four studies assessing data use by data and documentation either queried information directly from the data in the studied PHIS, if applicable, or collected evidence from related documents such as reports, summaries, and guidelines [78, 89, 99, 109]. The data to be collected included actioned requests, the number of data linked to action, and the number of data used for planning. Time for data collection varied without explanation, such as 12 months in ME PRISM or six years by Freestone et al. [78, 89].

#### 2.3.3.2.4 Data analysis methods

The data collected from qualitative studies were usually processed manually, organized thematically or chronologically. They were either analysed by classification of answers, grouping by facility or respondent's role, or categorization of verbatim notes into themes.

Various strategies were applied for quantitative data. For example, Wilkinson and McCarthy counted the same or similar responses to indicate frequency of beliefs/examples across participants [68]. Data in their study were analysed individually, by role and aggregated level. Some correlational analyses, such as Pearson's r for parametric data and Spearman's Rho for non-parametric data, were conducted to identify possible relationships between data use, perceptions of data, and organizational factors. Petter and Fruhling conducted hypothesis analysis in structured questionnaire with a 7-point Likert scale for all quantitative questions [100]. Due to the small sample size of 64 usable responses, they used summative scales for each of the constructs. All of the items used for a specific construct were averaged to obtain a single value for this construct. Then, using this average score, each hypothesis was tested using simple regression.

### 2.3.3.3 Methods for Assessment of the Dimension of Data Collection Process

Although the aim of assessing data flow or the process of data collection was only stated in two studies, another 14 articles were found that implicitly assessed data collection process [28, 29, 65, 78, 79, 82, 89, 92, 95-98, 103, 105, 107, 108]. These articles were identified through a detailed content analysis. For example, data collection process assessment activities were sometimes initiated by identification of the causes of poor data quality [89, 92, 96]. Or data collection process was considered as a component of the evaluation of the effectiveness of the system [28, 65, 79, 82, 95, 97, 103, 107]. Three studies led by two institutions, CIHI and MEASURE Evaluation Project, assessed data collection process while conducting assessment of the quality of the data [29, 78, 98]. Details are given in Appendix A Table A3.

#### 2.3.3.3.1 Quality attributes of data collection process and corresponding measures

A total of 23 attributes of data collection process were identified. These were: quality index or quality scores or functional areas, root causes for poor data quality, metadata or metadata documentation or data management or case detection, data flow or information flow chart or data transmission, data collection or routine data collection or data recording or data collection and recording processes or data collection procedures, data quality management or data quality control, statistical analysis or data compilation or data dissemination, feedback, and training.

Only four studies explicitly defined the attributes of the dimension of data collection process, two of them from institutions [78, 82, 89, 108]. Data collection was the most-used attribute in six publications [28, 78, 89, 103, 105, 107, 108]. The next most-assessed attribute is data management processes or data control reported in four publications [28, 82, 105, 107].

Data collection process was sometimes considered a composite concept in six studies, four of them proposed by institutions [28, 29, 79, 82, 95, 97]. For example, the quality index/score was composed of five attributes: recording practices, storing/reporting practices, monitoring and evaluation, denominators, and system design (the receipt, processing, storage and tabulation of the reported data) [79, 95, 97]. Metadata documentation or metadata dictionary cover dataset description, methodology, and data collection, capture, processing, compilation, documentation, storage, analysis and dissemination [29, 82]. The ME DQA assessed five functional areas, including structures, functions and capabilities, indicator definitions and reporting guidelines, data collection and reporting forms and tools, data management processes, and links with the national reporting system [28].

#### 2.3.3.3.2 Study design

Seven studies only used qualitative methods [89, 92, 96, 98, 103, 107, 108], five only conducted quantitative research [29, 65, 78, 95, 105], and four used both approaches [28, 79, 82, 97]. Questionnaire surveys were reported in 10 papers [28, 29, 65, 78, 79, 82, 95, 97, 105, 108]. Interviews were conducted in 3 studies [28, 98, 108]. Focus group approaches, including consultation, group discussion, or meeting with staff or stakeholders, were reported in four studies [82, 89, 96, 103]. Review of documentations was conducted in 5 papers [28, 78, 89, 92, 107], and field observation was used in 5 studies [28, 78, 89, 98, 103].

#### 2.3.3.3.3 Data collection and analysis methods

The study subjects included managers or users of the PHIS, the documentation of instructions and guidelines of data management for the PHIS, and some procedures of data collection process. The study subjects were entirely users in eight studies [29, 65, 78, 82, 95, 96, 105, 108]. Corriols *et al.* and Dai *et al.* only studied documentation such as evaluation reports on the PHIS including deficiency in the information flow chart and non-reporting by physicians [92, 107]. Data process was studied in six publications [28, 82, 89, 97, 98, 103]. Of these, four studies combined data process with users and documentations [28, 79, 89, 103], while Hahn *et al.* only observed data collection procedures and Ronveaux *et al.* surveyed users and observed data collection procedures for a hypothetical population [97, 98].

The data collection methods included field observation, questionnaire surveys, consensus development, and desk review of documentation. Field observations were conducted either in line with a checklist or in an informal way [28, 78, 89, 97, 98, 103]. Lin *et al.* made field observations of the laboratory staff dealing with specimens and testing at the early stage of the data collection process [103]. Freestone *et al.* observed data coders' activities during the process of data geocoding and entry [52]. Hahn *et al.* followed the work-through in study sites [98]. WHO DQA conducted field observations on sites of data collection, processing and entry [79], while Ronveaux *et al.* observed workers at the health-unit level who completed some data collection activities for 20 hypothetical children [97]. ME DQA made follow-up on-site assessment of off-site desk-reviewed documentation at each level of the PHIS [28].

Questionnaire surveys included semi-structured and structured ones [28, 29, 65, 78, 79, 82, 95, 97, 105, 108]. The questionnaire data were collected by face-to-face interviews, except one online questionnaire survey study by Forster *et al.* [105]. Five studies used a multi-stage sampling method [28, 65, 79, 95, 97]. The rest surveyed convenience samples or samples chosen according to a particular guideline, which was sometimes not described [28, 29, 78].

Consensus development was mainly used in group discussion and meetings, guided by either structured questionnaires or data quality issues [82, 96]. Ancker *et al.* held a series of weekly team meetings over about four months with key informants involved in data collection [96]. They explored the root causes of poor data quality in line with the issues identified from assessment results. WHO HMN organized group discussions with approximately 100 major stakeholders [82]. Five measures related to data collection process were contained in a 197-item questionnaire. The consensus to each measure was reached through self-assessment, individual or group scoring to yield a percentage rating [82].

Desk review of documentation was reported in six studies [28, 89, 92, 103, 107, 108]. The documentation included guidelines, protocols, official evaluation reports and those provided by data management units. The procedures for appraisal and adoption of relevant information were not introduced in the studies.

Data analysis methods for quantitative studies were mainly descriptive statistics. Most papers did not present the methods for analysis of the qualitative data. Information retrieved from the qualitative study was usually triangulated with findings from quantitative data.

### 2.3.4 Summary of the findings

Four major themes of the results have emerged after our detailed analysis, which are summarized in this section.

The first theme is there are differences between the seven institutional and the 32 individual research publications in their approach to data quality assessment, in terms of aims, context and scope. First, the effectiveness of the PHIS was more of an institutional rather than a researcher's interest. It was covered in all of the institutional publications but only in one-third of the research papers. Second, the disease-specific public health contexts covered by United Nations' MDGs, maternal health, children's health, and HIV/AIDS, were the area most often studied by researchers. Whereas the institutions also paid attention to

the routine PHIS. Third, the institutions tended to evaluate all levels of data management whereas most research studies were focused on a single level of analysis, either record collection or management.

The second theme is coverage of the three dimensions of data quality was not equal. The dimension of data was most frequently assessed (reported in 35 articles). Data use was explicitly assessed in five studies and data collection process in one. Implicit assessment of data use and data collection process was found in another five and 15 papers, respectively. The rationale for initiating these implicit assessments was usually to identify factors arising from either data use or data collection process while assessing the quality of data. Within studies that considered more than one dimension of data quality, 15 assessed both data and data collection process, seven assessed data and data use and one, both data use and data collection process. Only four studies assessed all three dimensions of data quality.

The third emerging theme is a lack of clear definition of the attributes and measurement indicators of each dimension of data quality. First, a wide variation of the definition of the key terms was identified, including the different terms for the same attribute, and the same term to refer to distinct attributes. The definition of attributes and their associated measures was sometimes given based on intuition, prior experience, or the underlying objectives unique to the PHIS in a specific context.

Second, the attributes of the quality of data were relatively developed than those for the dimensions of data use and data collection process. Most definitions of data quality attributes and measures are referred to the dimension of data as opposed to the other two dimensions, the attributes of which were primarily vague or obscure. One clear gap is the absence of the attributes of the dimension of data collection process.

Third, a consensus has not been reached as to what attributes should be measured. For example, a large variety existed in the number of attributes measured in the studies varied between 1 and 8, in a total of 49 attributes. The attribute of data quality in public health is often measured positively in terms of what it is. The three most-used attributes of good data quality were completeness, accuracy, and timeliness. The institutions tended to assess more attributes of data quality than individual researchers. The number of attributes reported in research papers was no more than four, while the institutions assessed at least four attributes.

The last emerging theme of the results is methods of assessment lack systematic procedures. Quantitative data quality assessment primarily used descriptive surveys and data audits, while qualitative data quality assessment methods include primarily interview, documentation review and field observation. Both objective and subjective strategies were identified among the methods for assessing data quality. The objective approach applies quantifiable measurements to directly examine the data according to a set of data items/variables/elements/tracer items. The subjective approach measures the perceptions of the users and stakeholders of the PHIS. However, only a small minority of the reviewed studies used both types of assessment. Meanwhile, field verification of the quality of data is not yet a routine practice in data quality assessment. Only five studies conducted field observations for data or for data collection process and they were usually informal. The reliability and validity of the study was rarely reported.

## 2.4 Discussion

Data are essential to public health. They represent and reflect public health practice. The broad application of data in PHIS for the evaluation of public health accountability and performance has raised the awareness of public health agencies of data quality, and of methods and approaches for its assessment. We systematically reviewed the current status of quality assessment for each of the three dimensions of data quality: data, data collection process and data use. The results suggest the theory of measurement has been applied either explicitly or implicitly in the development of data quality assessment methods for PHIS. The majority of previous studies assessed data quality by a set of attributes using certain measures. Our findings, based on the proposed conceptual framework of data quality assessment for public health, also identified the gaps existed in the methods included in this review.

The importance of systematic, scientific data quality assessment needs to be highlighted. All three dimensions of data quality, data, data use and data collection process, need to be systematically evaluated. To date, the three dimensions of data quality were not given the same weight across the reviewed studies. The quality of data use and data collection process has not received adequate attention. This lack of recognition of data use and data collection process might reflect a lack of consensus on the dimensions of data quality. Because of the equal contributions of these three dimensions to data quality, they should be given equal weight in data quality assessment. Further development in methods to assess data collection process and data use is required.

Effort should also be directed towards clear conceptualisation of the definitions of the relevant terms that are commonly used to describe and measure data quality, such as the dimensions and attributes of data quality. The lack of clear definition of the key terms creates confusions and uncertainties and undermines the validity and reliability of data quality assessment methods. An ontology-based exploration and evaluation from the perspective of data users will be useful for future development in this field [75, 113, 114]. Two steps that involve conceptualization of data quality attributes and operationalization of corresponding measures need to be taken seriously into consideration and rationally followed as shown in our proposed conceptual framework.

Data quality assessment should use mixed methods (e.g., qualitative and quantitative assessment methods) to assess data from multiple sources (e.g., records, organizational documentation, data collection process and data users) and used at different levels of the organization [38, 75, 76]. More precisely, we strongly suggest subjective assessments of end-users' or customers' perspectives be an indispensable component in data quality assessment for PHIS. The importance of this strategy has long been articulated by the researchers [38, 75, 76]. Objective assessment methods assess the data that were already collected and stored in the PHIS. Many methods have been developed, widely accepted and used in practice [75]. On the other hand, subjective assessments provide a supplement to objective data quality assessment. For example, interview is useful for the identification of the root causes of poor data quality and for the design of effective strategies to improve data quality. Meanwhile, field observation and validation are necessary wherever it is possible because reference of data to the real world will give data users confidence in the data quality and in application of data to public health decision-making, action, and outcomes. The validity of a study would

be doubtful if the quality of data could not be verified in the field [76], especially when the data are come from a PHIS consisting of secondary data.

To increase the rigor of data quality assessment, the relevant statistical principles for sample size calculation, research design, measurement and analysis need to be adhered to. Use of convenience or specifically chosen sampling methods in 24 studies included in this review reduced the representativeness and generalizability of the findings of these studies. At the same time, reporting of data quality assessment needs to present the detailed procedures and methods used for the study, the findings and limitations. The relatively simple data analysis methods using only descriptive statistics could lead to loss of useful supportive information.

Finally, to address the gaps identified in this review, we suggest re-prioritizing the orientation of data quality assessment in future studies. Data quality is influenced by technical, organizational, behavioural and environmental factors [30]. It covers large information systems contexts, specific knowledge and multi-disciplinary techniques [30]. Data quality in the reviewed studies is frequently assessed as a component of the quality or effectiveness or performance of the PHIS. This may reflect the major concern of public health is in managerial efficiency, especially of the PHIS institutions. Also, this may reflect differences in the resources available to, and the responsibilities of institutions and individual researchers. However, data quality assessment hidden within other scopes may lead to ignorance of data management and thereby the unawareness of data quality problems enduring in public health practice. Data quality needs to be positioned at the forefront of public health as a distinct area that deserves specific scientific research and management investment.

While this review provides a detailed overview of data quality assessment issues, there are some limitations in its coverage, constrained by the access to the databases and the breadth of public health information systems making it challenge to conduct systematic comparison among studies. The search was limited by a lack of subject headings for data quality of PHIS in MeSH terms. This could cause our search to miss some relevant publications. To compensate for this limitation, we used the strategy of searching well-known institutional publications and manually searching the references of each article retrieved.

Our classification process was primarily subjective. It is possible that some original researchers disagree with our interpretations. Each assessment method has contributions and limitations which make the choices difficult. We provided some examples of approaches to these issues.

In addition, our evaluation is limited by an incomplete presentation of details in some of the papers we reviewed. A comprehensive data quality assessment method includes a set of guidelines and techniques that defines a rational process to assess data quality [38]. The detailed procedure of data analysis, data quality requirements analysis, and identification of critical attributes is rarely given in the reviewed papers. A lack of adequate detail in the original studies could have affected the validity of some of our conclusions.

## 2.5 Conclusions

Public health is a data-intensive field which needs high-quality data to support public health assessment,

decision-making and to assure the health of communities. Data quality assessment is important for public health. In this review of the literature， we have examined the data quality assessment methods from the three dimensions of data quality: data, data use and data collection process. We found that the dimension of the data themselves was most frequently assessed in previous studies. Most methods for data quality assessment evaluated a set of attributes using relevant measures. Completeness, accuracy, and timeliness were the three most-assessed attributes. Quantitative data quality assessment primarily used descriptive surveys and data audits, while qualitative data quality assessment methods include primarily interview, documentation review and field observation.

We found that data-use and data-process have not been given adequate attention, although they were equally important factors which determine the quality of data. Other limitations of the previous studies were inconsistency in the definition of the attributes of data quality, failure to address data users' concerns and a lack of triangulation of mixed methods for data quality assessment. The reliability and validity of the data quality assessment were rarely reported. These gaps suggest that in the future, data quality assessment for public health needs to consider equally the three dimensions of data quality, data, data use and data process. More work is needed to develop clear and consistent definitions of data quality and systematic methods and approaches for data quality assessment.

The results of this review highlight the need for the development of data quality assessment methods. As suggested by our proposed conceptual framework, future data quality assessment needs to equally pay attention to the three dimensions of data quality. Measuring the perceptions of end users or consumers towards data quality will enrich our understanding of data quality issues. Clear conceptualization, scientific and systematic operationalization of assessment will ensure the reliability and validity of the measurement of data quality. New theories on data quality assessment for PHIS may also be developed.

# Chapter 3 Identification of essential quality components in the data collection process for public health information systems

## Foreword

The previous chapter proposed a three-dimensional (3D) framework for PHIS data quality assessment, including the quality of data, the quality of the data collection process and the quality of data use. Following the 3D framework, a systematic review of the extant data quality assessment methods for PHIS revealed a practice gap and essential need for measuring the quality of the PHIS data collection process. This chapter is an extensive review of the literature about the factors that affect the quality of the PHIS data collection process to conceptualize a framework to measure the process. A five-stage qualitative healthcare data analytic framework suggested by Pope et al [22] helps analyse, synthesize and identify the essential components in the data collection process. A preliminary framework containing four essential components, 12 subcomponents and 149 items emerges. For ease of understanding and use, the framework uses the term 'dimension' to categorize the four components though the quality of the data collection process is indeed one of the three dimensions of data quality; thus, the framework is named 4D component framework.

This chapter is a reproduction with minor corrections of the published full paper "Identification of the essential components of quality in the data collection process for public health information systems" authored by Hong Chen, Ping Yu, David Hailey, and Tingru Cui, and published in Health Informatics Journal 2020;26(1): 664-682. doi: 10.1177/1460458219848622.

The Table and Figure numbers, the Reference numbers and the Section numbers have been adjusted to fit within the structure of the thesis.

## Abstract

This study identifies essential components in the data collection process for public health information systems based on appraisal and synthesis of the reported factors affecting this process in the literature. Extant process assessment instruments and studies of public health data collection from electronic databases and the relevant institutional websites were reviewed and analysed following a five-stage framework. Four dimensions covering 12 factors and 149 indicators were identified. The first dimension, data collection management, includes data collection system and quality assurance. The second dimension, data collector, is described by staffing pattern, skill or competence, communication, and attitude towards data collection. The third, information system, is assessed by function and technology support, integration of different data collection systems, and device. The fourth dimension, data collection environment, comprises training, leadership, and funding. With empirical testing and contextual analysis, these essential components can be further used to develop a framework for measuring the quality of the data collection process for public health information systems.

Keywords: data collection, data quality, measurement instrument, process assessment, public health information systems

## 3.1 Introduction

Public health information systems (PHIS), the government recognized population-based data repositories, are essential for public health management and improvement [51]. PHIS provide nations with health-related data mainly required for monitoring, prevention and control of diseases and other adverse health conditions [115]. Data in PHIS must be of sufficient quality to meet public health needs and worthy of data users' trust [1, 29, 32, 116, 117]. The World Health Organization (WHO) has introduced a generic Data Quality Assessment Framework (DQAF) developed by the International Monetary Fund [1]. The WHO has reinforced that data quality assessment should not only describe the quality status of data but also enable identification of the causes of data quality problems [1, 2]. The process of data collection is an essential element of data quality. It includes the generation, assembly, description, and maintenance of data, all of which should be of high quality [30, 31]. While data quality problems originating from the process of data collection have been frequently found, research into this topic area is yet to further develop [32, 33].

To date, the assessment of the quality of the data collection process in PHIS has not been well considered nor routinely conducted [31]. The quality improvement effort has been focused on assessment of the quality of data which have already been captured and stored [29, 31, 34]. Data quality assessment is mainly focused on the identification and evaluation of the attributes of data quality, including accuracy, completeness, and timeliness of data [31, 41, 118]. The reason for the lack of attention to the quality of the data collection process could be an insufficient clarification of the essential components for data collection. For example, our review of PHIS data quality assessment showed that only two (5%) of 39 studies specified an explicit definition of the quality of data collection [31]. A variety of quality criteria for data collection were introduced such as data accuracy, data integrity, minimum response burden for data-provider practices, and

the relevance, simplicity, and layout of the data collection tools [29, 32, 35, 36].

Data collection is a systematic data gathering process [35], which includes a set of interrelated or interacting activities contributing to the process of transforming inputs into outputs [37]. Organizational, technical and behavioural factors can affect the performance of the data collection process for the PHIS [32, 33, 38-41]. They may "take the form of defects in organizational procedures, faulty logic, and reasoning, or human error that result in compromised performance" [42]. 16 of the 39 implementation studies reviewed in our earlier study, instead of taking a comprehensive picture of the entire process, were centred around some data collection procedures, such as data recording and storage, and on quality control mechanisms [31]. The unsystematic knowledge about the key factors influencing the quality of the data collection process has impaired the effectiveness and efficiency of data-driven monitoring and performance evaluation mechanisms for public health programs [32, 33, 42, 43].

An interesting question is: *what are the exact components to ensure the quality of the data collection process*? Researchers have conducted some exploration in this area. At the organizational level, structure, resources, procedures, support services, and culture in an organization can all influence the process quality of data collection [38-41]. However, the operational definition or measurement for these factors has yet to be reached. At the technical level, the design of electronic data collection forms and integration of different information systems are important mechanisms. But technology advancement alone cannot always lead to high-quality data [32, 33, 41, 42]. At the individual behavioural level, a data collector's motivation and competence to perform a task, though often scrutinized from the lens of data users, have not been clarified in the context of the data collection process [41]. The lack of a comprehensive understanding of the contribution of these factors leads to challenges in assessing the quality of that process.

Such challenges hence pose the fundamental research question of this study which aims to identify the essential components of quality in the data collection process for PHIS.

## 3.2 Methods

### 3.2.1 Literature search

We searched peer-reviewed full-text English literature in medical and informatics electronic databases, including Scopus, CINAHL, Medline, PubMed, and Web of Science. The publication dates were from January 1, 2001 (since the principles and practices of PHIS were defined in the discipline of public health informatics [119]) to December 31, 2016. Search terms included words or phrases relating to data collection, process assessment, measurement, data quality, public health, and health information systems. The symbol "*" was used to include the variations of a word. A total of 172 publications were retrieved.

To improve the literature coverage, we further conducted a manual search of the literature and identified papers referenced by the selected publications. Prominent public health institutional websites were also searched, such as those of the WHO and the Australian Institute of Health and Welfare (AIHW). The

authors' research databases on data quality assessment were also searched. Another 52 publications from these sources were included. Two of the authors independently assessed the study quality. Any discrepancies were resolved through discussion and an informal consensus process.

### 3.2.2 Selection of publications

Articles were assessed based on inclusion and exclusion criteria. The inclusion criteria were articles contributing significantly in the domain of quality of the data collection process in the PHIS; and research topics related to the quality of the data collection process. The article types included empirical studies, reviews, guidelines and work reports.

The exclusion criteria were publications that did not mention factors or components of the quality of the data collection process; those focusing on data use or only measuring the data stored in the PHIS; and those lacking clear definition or without evidence-based information. Editorials, notes, and letters were also excluded.

The above screening activities led to a selection of 107 articles eligible for further study quality evaluation.

We used the Critical Appraisal Skills Program (CASP) tools to assess the reliability and validity of each selected study [18, 19]. The CASP tools provide a set of checklists for evaluation of study quality including the context, subjects, study design, research methods, data collection, data analysis, and conclusions.

We also considered: (1) whether the concepts of data quality or the quality of the data collection process matched our understanding of these; (2) whether the cause of poor data quality arising from the data collection process was analysed; and (3) how the factors contributing to the quality of data collection or data quality were measured. The studies that did not provide adequate information and rigorous research methods, were excluded.

Eventually, 45 publications were selected for review. The publication selection and evaluation process are illustrated in Figure 3-1.

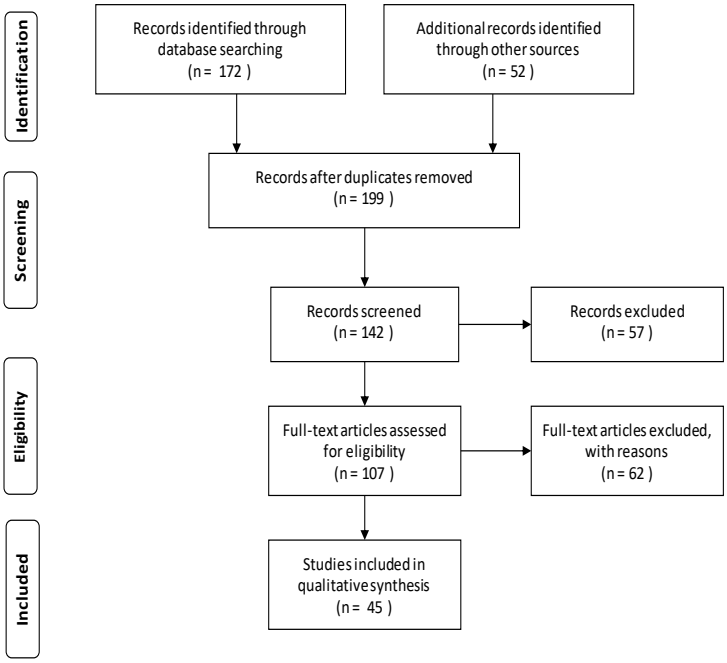


Figure 3-1 Publication selection process

### 3.2.3 Data extraction and analysis

A five-stage framework was followed for qualitative data extraction, processing and analysis [22].

Stage 1. Familiarization with data. Each article was thoroughly read to identify quality issues, concepts, and themes related to the data collection process. Relevant data from the selected studies were extracted and entered into an Excel spreadsheet to facilitate critical evaluation of the results. A total of 453 pieces of relevant text were pre-selected and recorded.

Stage 2. Identification of a thematic framework. A process of shortening the extracted text while still preserving the core was conducted for condensing the relevant data. A constant comparison and aggregation process led to the abstraction of 149 first-level codes as indicators relating to the quality of the data collection process. Further comparison, aggregation, abstraction, and classification of the indicators generated 16 factors that were related to the quality of the data collection process. These factors were further abstracted using an approach based on general systems theory [120] and advice from public health experts. A four-dimensional thematic framework was developed, including data collection management, data collector, information system and the data collection environment.

Stage 3. Indexing and validation of the thematic framework. The process of constant comparison, aggregation, and classification was iterated repetitively. Data were re-arranged per the appropriate dimension of the thematic framework to which they were likely to belong. Attempts were made to avoid duplication and overlap in semantics and refinement of paraphrasing within the framework. This process led to the reduction of factors from 16 to 12.

Stage 4. Charting. The 12 factors were arranged into the appropriate dimension of the thematic framework

to which they related. A chart was prepared.

Stage 5. Mapping and interpretation. This stage is a process to map the nature and range of the concepts and factors. The associations between the factors were identified to create the typology of the framework. Each indicator was interpreted as either a facilitator or a barrier according to its direction of influence, positive or negative, on the quality of the data collection process. Eventually, the theoretical saturation was reached, and all extracted data were placed into the categories already created (Table 3-1).

Table 3-1 Data for the 45 included studies

| Author, publication year | Region | Characteristics of study | Themes | Association with data quality |
|---|---|---|---|---|
| Abernethy et al. 2011 [121] | USA | 1. Surveyed tuberculosis contact investigation forms from all fifty states, three municipalities and two countries. 2. Apply statistics and cluster analysis. | A C | 1. Standardization of data elements. 2. Quantitative data analysis. |
| Ahanhanzo et al. 2014 [122] | Benin | 1. Cross-sectional descriptive and analytical study of factors associated with data quality in the routine health information systems. 2. Data including (1) document review of data, (2) self-administered questionnaire, and (3) focus groups with 116 health workers in 4 municipalities. 3. Apply statistics and qualitative analysis. | B | 1. Data comprehensiveness, reliability and accuracy. 2. Significant difference by statistical quantitative data analysis. |
| Aidara et al. 2011 [123] | Eight European countries | A clinical survey was completed for 146 sentinel dentists in eight European countries and included 2877 clinical examinations and 2877 individual assessments. | A B D | 1. Missing data and time for data collection. 2. Descriptive correlational statistical analysis. |
| Amouzou et al. 2014 [124] | Malawi | 1. Comparison of children mortality monitoring data reported by 160 community health workers and those computed in a standard household mortality survey. 2. Data analysis by using rates, standard errors, and 95% confidence interval. | A D | 1. Data accuracy and completeness. 2. Descriptive quantitative statistics. |
| Anderka et al. 2015 [125] | USA | 1. A descriptive study to develop and test a data quality assessment tool for population-based birth defect surveillance programs. 2. Assessment by a self-administered (with no evaluation component) Standards Data Quality Assessment Tool about National Birth Defects Prevention Network (NBDPN). | A B D | 1. Data completeness, timeliness, and accuracy. 2. No statistical association analysis was conducted. |
| Andersson et al. 2003 [126] | Sweden | 1. Cross-sectional case study in process-oriented healthcare organizations. 2. Data collected (1) from archives, (2) through interviews, (3) by participatory observation, and (4) by conducting a focus group session. 3. Use of descriptive | A B C D | Not provided. |

| | | | | |
|---|---|---|---|---|
| | | qualitative data. | | |
| Bosch-Capblanch et al. 2008 [95] | Forty-one low income countries | 1. Cross-sectional study using the Data Quality Audit (DQA) a WHO validated, standard methodology to compare data collected from health unit (HU) records of immunizations administered with reports of immunizations at central level and to collect quality indicators of the reporting system. 2. Statistical analysis of quality scores and data verification results. | A C | 1. Data accuracy (verification factor, VF). 2. No significant correlation between data accuracy with national quality scores while significant correlations with districts and health unit's quality scores. |
| Braa et al. 2012 [127] | United Republic of Tanzania | 1. An action research conducted at 10 districts, delivering interventions by quarterly data-use workshops focusing on data collection, integration, data quality, teamwork, practical computer skills, and presentation skills. 2. Use of descriptive qualitative data. | A B C D | 1. General data quality. 2. Improvement of general data quality was supported by descriptive qualitative data. |
| Bradley et al. 2014 [128] | Peru | 1. A descriptive study to assess data quality of a perinatal syphilis information system. 2. Data collected by (1) records review in 43 of 156 public hospitals, (2) 8 in-depth interviews with stakeholders. 3. Descriptive statistic data analysis. | A C D | 1. Data quality and completeness. 2. Qualitative reasoning while no statistical association analysis was conducted. |
| Chen et al. 2014 [31] | International | 1. Comparative study. 2. Use of descriptive qualitative data. | A | Not provided. |
| Chisha et al. 2015 [129] | Zambia | Intervention of enhanced surveillance and data feedback loop. | A D | 1. Data completeness, accuracy, consistency. 2. Descriptive correlational statistical analysis. |
| Cibulskis and Hiawalyer, 2002 [130] | Papua New Guinea | 1. Program report of national health management information systems relating to standardization of the system design, test, implementation, integration of different systems and using information of a national health information system. 2. Use of descriptive qualitative data. | A B C D | Not provided. |
| Corriols et al. 2008 [92] | Nicaragua | 1. A nationally representative cross-sectional survey of 3,169 persons aged 15 years and older. 2. Review official evaluations of the pesticide poisoning surveillance system to understand what | B D | 1. Underreporting of data. 2. No statistical association analysis |

| | | | | |
|---|---|---|---|---|
| | | caused the underreporting. 3. Use of quantitative and qualitative data. | | was conducted. |
| DiGiacomo et al. 2010 [131] | Australia | 1. Cross-sectional descriptive study of the implementation of the national guidelines in cardiac rehabilitation. 2. Data collected by semi structured interviews with 37 health professional's perspectives of systems-related barriers to implementation of the national guidelines. 3. Use of descriptive qualitative data. | A B C D | Not provided. |
| Galvin et al. 2015 [132] | Ireland | 1. Extract data using a software. 2. Evaluate extracted data from 30 practices in line with 12 European quality indicators. 3. Comparative analysis between seasons and regions. | C | 1. Data accuracy and variation. 2. Descriptive statistics without correlational analysis. |
| Hajdu et al. 2011 [133] | Norway | 1. Use USCDC Guidelines for the evaluation of point-prevalence of healthcare-associated infections in hospitals and long-term care facilities for elderly surveillance systems. 2. Data collected by review of surveillance protocol and database, and survey with data mangers and practitioners. | A C D | 1. Data completeness. 2. Descriptive statistics. |
| Haskew et al. 2015 [134] | Kenya | 1. Use a two-sample test of proportions pre- and post-implementation of EMR-based data verification. 2. Significant improvements in completeness of the antenatal record were recorded. | C | 1. Data completeness. 2. Significant difference by statistical quantitative data analysis. |
| Haswell et al. 2013 [135] | Australia | 1. Intervention of using an indigenous register within a psychiatric hospital information system. 2. Cross-validation of health information system data with the indigenous register over 2 years about 355 indigenous admissions. 3. Use of quantitative data. | A B C D | Data accuracy (increased accuracy and reliability of data by descriptive quantitative statistics). |
| Heidebrecht et al. 2012 [136] | Canada | 1. A feasibility study of scannable forms in two settings. 2. Assessment of efficiency, data quality, and usability through time observations, record audits, staff interviews, and client surveys. 3. Use of quantitative and qualitative data. | C | 1. Efficiency of data entry. 2. Agreement (consistency) of data. 3. Quantitative statistics and qualitative data. |
| Heidebrecht et al. 2014 [118] | Canada | 1. Cross-sectional descriptive study of electronic immunization data collection systems in two Ontario public health units. 2. Use of an adapted Centers for Disease Control and Prevention surveillance system evaluation guidelines (USCDC Guidelines). 3. Data collected by key informant interviews, logic and completeness | A B C D | 1. User's perception of simplicity and flexibility of data input and report access. 2. Data completeness and validity, timeliness. |

| | | | | |
|---|---|---|---|---|
| | | assessments, client surveys, and on-site observations. 4. Use of quantitative and qualitative data. | | 3. No statistical association analysis was conducted. |
| Ing et al. 2014 [137] | Canada | 1. Qualitative study of barriers experienced, and the techniques used to overcome barriers during investigation of enteric disease cases among expert investigators. 2. Four focus groups, 28 experts involved via teleconference; data from cases was thematically analyzed. | C D | Not provided. |
| Kaposhi et al. 2015 [138] | South Africa | 1. Cross-sectional descriptive study. 2. Data audits and semi-structured interviews by adapting an international routine data quality assessment tool in 32 facilities in 3 sub-districts. 3. Use of quantitative and qualitative data. | A B C D | 1. Data accuracy described with quantitative data audit. 2. No statistical association analysis was conducted. |
| Kawonga et al. 2012 [139] | South Africa | 1. Cross-sectional descriptive study. 2. Data collected by key informant interviews with managers and review of records, observation. 3. Use of quantitative and qualitative data. | A | Not provided. |
| Kiilu et al. 2015 [140] | Kenya | 1. Cross-sectional study of assessing health workers skills and current training needs for information management by purposive sampling of 121 health workers. 2. Data collected by self-administered open-ended and closed-ended, structured questionnaires. 3. Quantitative data analysis. | B | 1. Data accuracy. 2. Status of data quality was not provided. |
| Krenzelok et al. 2014 [141] | USA | 1. Deliver an intervention of a two-tiered intervention program (passive and interactive training) to enhance the quality of data collection using acetaminophen exposures as a model. 2. Data collected by a quality-measurement scorecard. | C | Data accuracy of some data items with significant difference by statistical quantitative data analysis. |
| Ledikwe et al. 2014 [142] | Botswana | 1. A qualitative assessment of the health data management and reporting systems that capture and transfer routine monitoring and evaluation (M&E) AIDS data by using Routine Data Quality Audit Tool (MEASURE Evaluation). 2. Data collected by 71 in-depth interviews and over 300 reference materials. 3. ATLAS (Version 6.1, Scientific Software Development) was used to assist with systematic analysis of the qualitative data. | A B C D | Not provided. |
| Lin et al. 2012 [103] | China | 1. Use the USCDC Guidelines to assess the performance of the national HIV sentinel surveillance system (HSS). 2. Data collected by using a detailed checklist to review surveillance | A C D | 1. Data completeness and accuracy. 2. No statistical |

| | | | | |
|---|---|---|---|---|
| | | guidelines, protocols and relevant documents; conducting self-administered, anonymous surveys with 286 local China CDC staff; and carrying out field observations in 32 sentinel sites in four provinces. | | association analysis was conducted. |
| Lowe et al. 2014 [143] | USA | 1. A retrospective review of the introduction of tan electronic health record system. 2. Use descriptive quantitative data. | C | 1. Efficiency of data collection. 2. Descriptive statistical analysis. |
| Madsen et al. 2007 [144] | Europe | Report on the manual of operations. | A | Not provided. |
| Melnik et al. 2015 [145] | USA | Cross-sectional descriptive study to identify current practices and potential barriers to accurate and complete data collection by birth registrars (BRs) in New York State facilities and data collected by a piloted and tested questionnaire survey on 127 birth registrars from New York City and the Rest of State. | A B C D | Data accuracy and completeness with statistical analysis. |
| Mphatswe et al. 2012 [146] | South Africa | 1. Intervention of prevention of mother-to-child transmission (PMTCT) of the human immunodeficiency virus using a series of strategies including training, feedback, monthly data reviews and data audits at facilities over ten months in 8 antenatal clinics and 20 delivery wards (37 urban, 21 rural and 20 semi-urban) in a province. 2. Data completeness and accuracy was compared before and after intervention. 3. Use of quantitative data. | A D | Data accuracy and completeness with statistical analysis. |
| Murai et al. 2011 [147] | Philipp ine | 1. Investigate the mechanisms of errors in the case identification process in the existing routine health information system (RHIS) by cross-sectional descriptive case study and data collected by a structured questionnaire by measuring the level and disparity of 132 health workers' (who were in charge of the case identification step) understanding of the definitions of 12 health program indicators in 14 selected municipalities in the province of Palawan. 2. Use of quantitative data. | A B C D | Data accuracy with statistical analysis of quantitative data |
| Mykkänen et al. 2007 [148] | Finlan d | 1. Description of current status and issues and a set of recommendations related to the standardization of healthcare. 2. Data collected by web-based survey to named experts in different organizations. | A C D | Not provided. |
| Nicol et al. 2013 [149] | South Africa | 1. Cross-sectional descriptive study using the Performance of Routine Information System Management (PRISM) tool. 2. Data collected by a self-administered questionnaire with 161 health information personnel in 58 health facilities and 2 | B | Not provided. |

| | | | | |
|---|---|---|---|---|
| | | district offices from 2 conveniently sampled health districts. 3. Use of quantitative data. | | |
| Paterson et al. 2012 [150] | Pacific Island Countries and Territories (PICTs) | 1. An in-country quantitative and qualitative evaluation in five PICTs by using the USCDC guidelines. 2. Data collected by semi-structured key informant interviews, observational techniques including field inspections of raw data and data collection methods, and analysis of syndromic data reported. | A B C D | Not provided. |
| Puttkammer et al. 2016 [151] | Haiti | A mixed-methods evaluation of a multi-site electronic medical record system using a qualitative Delphi process to identify data quality priorities among local stakeholders, and a quantitative data quality assessment (DQA) examined 13 indicators of completeness, accuracy, and timeliness of retrospective data collected from 2005 to 2013. | A C D | 1. Data completeness. 2. No statistical association analysis was conducted. |
| Reilly et al. 2011 [152] | USA | Program report of quality of care and case documentation by a two-part review process: a qualitative case review by independent reviewers and an administrative review of required documentation in the physical case record. | A B C D | 1. Data timeliness and completeness. 2. Qualitative review and quantitative statistical analysis. |
| Rimando et al. 2015 [153] | USA | Qualitative study of the data collection challenges in dissertation research by sharing experience of eight doctoral students. | A D | 1. General data quality. 2. Status of data quality was not provided. |
| Schuurman et al.2011 [154] | South Africa | A pilot study by analysis of the dataset to develop injury data collection protocols appropriate to low-resource environments, building on previous developments in the field such as those described previously. | A C D | Not provided. |
| Soti et al. 2015 [155] | Kenya | 1. A pilot study by implementation of a system the web portal to cloud based information. 2. Evaluate data accuracy, completeness and timeliness using descriptive statistics. | C | 1. Accurate, complete and timely data. 2. Descriptive statistics without correlational analysis. |
| Sychareun et al. 2013 [156] | Lao PDR | Retrospective review of data by compiling the data into a standardized excel sheet as well as making copies of health center data for verification. | A B C | 1. Data consistency, accuracy, security, availability, representation. 2. Simple descriptive statistical analysis. |

| | | | | |
|---|---|---|---|---|
| Tamrat et al. 2012 [157] | International | Literature review. | C | Not provided. |
| West et al. 2004 [158] | Scotland | 1. Program report of feedback interviews with 33 primary health care staff following service implementation of a computerized information system to collect workload data. 2. Use of qualitative data. | B D | Not provided. |
| Wilkins et al. 2008 [159] | International | 1. To develop a model for a data-driven health system assessing areas that impede decision makers' access to information. The Data for Decision Making (DDM) surveillance assessment methodology was applied to six systems in five countries. 2. Data collected by interviews and review of the data collection methods. | A B C D | 1. Data timeliness and accuracy. 2. Simplicity, flexibility, acceptability, and usefulness of the system. 3. Qualitative analysis. |
| Yourkavitch et al. 2016 [160] | Malawi | 1.Review integrated community case management data quality and the monitoring and evaluation (M&E) system using adapted Measure Evaluation "data quality audit tool". 2. Randomly selected sample facilities. 3. Use of quantitative and qualitative data. | A B C D | 1.Data accuracy, timeliness, completeness, confidentiality, reliability, precision, integrity, and availability. 2. Quantitative and qualitative analysis. |

Note: Column theme included A: Data collection management; B: Data collector; C: Information system; D: Data collection environment

## 3.3 Results

The results from the qualitative data processing and analysis provided material for the identification of the essential components of quality in the data collection process for PHIS, including four dimensions that covered 12 factors (Figure 3-2). The first dimension, data collection management, includes data collection system and quality assurance. The second dimension, data collector, is described by staffing pattern, skill and competence, communication, and attitude towards data collection. The third, information system, is assessed by function and technology support, integration of different data collection systems, and devices. The fourth, data collection environment, comprises training, leadership, and funding. The 12 factors are characterized by 149 indicators with either positive or negative impacts on the quality of the data collection process.

Accuracy, completeness, and timeliness are the most frequently mentioned parameters of quality for evaluating the performance of the data collection process. These three parameters appeared in 24, 16 and 7 studies, respectively. Fourteen studies did not define data quality specifically. Reliability, data use, quality of service and system quality were also addressed.

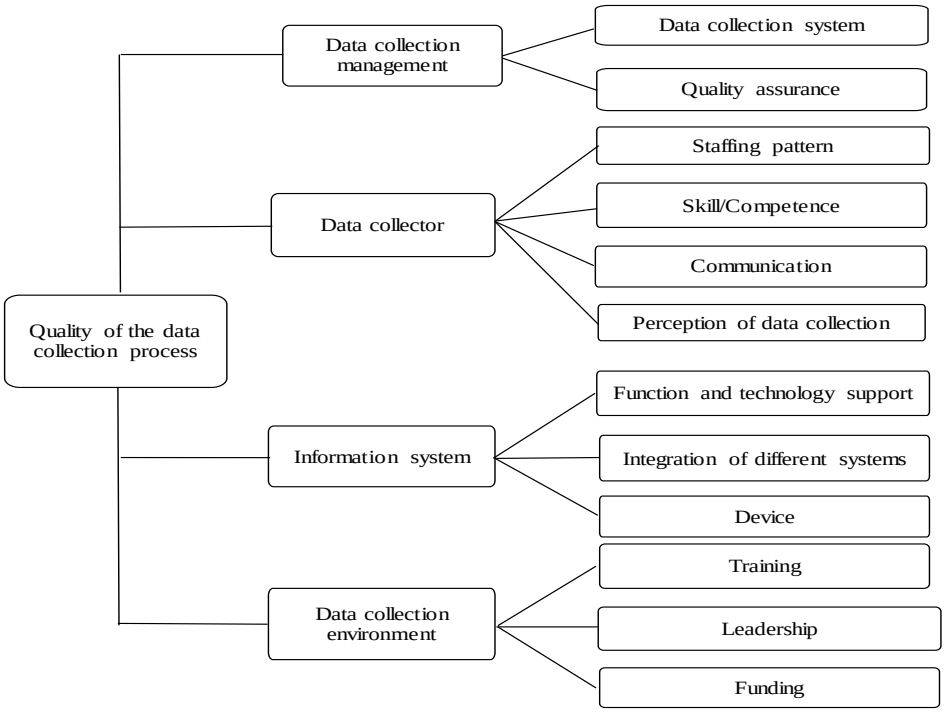


Figure 3-2 The components of the quality of the public health information system data collection process

### 3.3.1 Data collection management

From an organizational perspective, data collection management is an administrative process by which data are acquired, validated, stored, protected, and processed [32, 33]. Effective management requires the application of knowledge, skills, tools, and techniques to data collection activities to meet data quality requirements. The ultimate goal of data collection management is to fulfil every requirement from data users [33, 36]. That is the provision of sufficient supervision to personal and systematic process audits to ensure data quality. Thirty-two of the 45 included articles assessed the quality of data collection management [31, 95, 103, 118, 121, 122, 124-131, 133, 135, 138, 139, 142, 144-148, 150-154, 156, 159, 160] (Table 3-1).

For the preservation of data integrity, data collection management needs to detect errors that have occurred in the data collection process [36]. Errors may be produced intentionally (i.e., deliberate falsification) or unintentionally (i.e., systematic or random errors) [36]. In public health, data collection management primarily focuses on the procedures of data collection, storage, quality control, and data presentation for users [29, 117]. They are often presented in a format of guidelines or a set of policies to direct the execution of programs and guide the practice of parties involved in the process [29, 146]. We identified two major factors for data collection management in the context of the PHIS. They are data collection system and quality assurance.

A data collection system primarily comprises two subcomponents: data collection form and data collection practice. Data collection form is the core component of data collection instruments. A poorly-designed data collection form may impair data accuracy [159]; therefore, data collection form needs to be standardized,

well defined and structured. As one of the major concerns, standardization in the data collection form can be facilitated by a series of tactics [149]. The format of the data collection form needs to be simple, standardized, and complete [121, 125, 145]. The layout and order of data items of a form need to accord with the workflow of data capture or reporting for easy data entry and retrieval [95, 126].

Data collection practice should be well guided, conducted and documented. They include guideline development, documentation, data backup and security, selection of data collection methods, and a trial of a new process before implementation [130, 132, 135, 144]. A complete record of the data collection process in line with the workflow of data collection is recommended [138].

Quality assurance for data collection should be in place before collection begins and it should be focused on quality control [36, 148]. The function of quality assurance is to ensure each process of data collection is traceable, accurate and timely, and has integrity. Four factors could be utilized to assess the adequacy of system for quality assurance. These are quality audit, fundamental responsibility, mechanisms for addressing data quality challenges, and a feedback loop [118, 127, 129, 138]. Designated unit or individuals to monitor data quality and prevent data collection mismanagement are recommended. A veteran health worker register could remind data collectors to correct inaccurate data items and provide additional training, supervision, and incentives [124, 135, 152]. Holding regular meetings with medical or clinical staff and a data registrar is useful to address missing or inconsistent data [125, 147].

### 3.3.2 Data collector

A data collector collects or supplies data for the PHIS. Twenty-three of the 45 articles assessed the performance of data collectors [92, 118, 122-124, 126, 127, 130, 131, 135, 137, 138, 140, 142, 145, 147, 149, 150, 152, 156, 158-160] (Table 3-1).

A data collector is a stakeholder with whom the data user should build up and nurture a relationship. Data collectors' performance was mainly related to data accuracy [135, 138, 145, 147, 156, 159, 160]. The association between data quality and of the data collector's certain characteristics such as level of responsibility, level of work engagement and sector of employment was statistically quantified [122]. Four types of factors including the staffing pattern, their data collection skills or competence, communication with clients, and their attitude towards data collection could, directly and indirectly, influence data collectors' performance. For example, data collector shortage and high turnover could impair data quality [156]. A data collector needs to have sufficient capability to conduct capability to conduct data collection activities, e.g., understanding contextual information and having basic knowledge of the data elements to be collected. Proficient data collection skills and good communication with clients are ideal for a data collector. Mistakes often originated from data collectors' attempts to simplify data collection tasks. Provision of training is regarded by higher authorities and upper management as a useful approach to improving data collectors' capabilities including fundamental medical knowledge and routine data management skills [145, 147].

### 3.3.3 Information system

An information system is a combination of hardware, software, infrastructure, and trained personnel [29]. Thirty of the 45 articles assessed the quality of information systems [95, 103, 118, 121, 126-128, 130-136, 138, 139, 142, 143, 145, 147, 148, 150-152, 154-157, 159, 160] (Table 3-1). A regular system of data quality checks may be more cost-effective and reliable to ensure data quality [142].

Characteristics of information systems in PHIS are demonstrated by automatic functions and technology support provided to the users of the system, and the integration of different data collection systems and devices.

The functions of information systems in PHIS are automatic data processing, usually via an electronic interface of data collection forms and prompts for data collectors about data collection activities. The systems may automatically check the logic of data, assess the comprehensiveness of required data items, and issue alerts for errors made during data entry. These functions serve as an online task reminder to help with task completion and prevent slippage. Use of the "smart chart" technology can prevent a data collector from submitting a record with missing fields. In this manner, the function of an automatic logic check and smart selection of data are integrated into the mandatory fields. It is found that data errors are rare since the introduction of "smart charts". If an automatic workflow chart is available in the system, it could guide and standardize the data collection and reporting process. However, changes in the project procedures and system configuration over time may lead to a decline in data quality if deployed against established guidelines or specifications on data collection for PHIS.

Integration of different systems is important in the PHIS. Multiple systems and files may impair the quality of the data collection process if data are from the various sources. Therefore, centralizing data in one unique source and use of linked data systems is preferred. For example, the use of external data linkage and collaboration with other jurisdictions can facilitate the generation of a higher-level data repository or data sharing platform [118, 130].

Devices are the hardware used to store or transmit data such as computers, printers, and other electronic equipment. These devices need to be adapted to the operational system, suitable for use in data collection, and free from computer crashes, viruses and insecure methods for data backup and storage [131, 142, 148, 155, 157].

### 3.3.4 Data collection environment

Data collection environment refers to the context for data collection. In a government context, the PHIS is directly responsible to legislative, regulatory, and policy directives [51]. Thirty of the 45 articles assessed the quality of data collection environment [92, 103, 118, 122, 124-131, 133, 135, 137, 138, 141, 142, 145-148, 150-154, 158-160] (Table 3-1). Training, leadership, and funding support are the three main factors.

Training is imparting information and providing instructions to help trainees attain a required level of knowledge and skill or improve their performance. Such training should be mandated by higher authorities

and upper management, instead of on a voluntary basis [147, 161] Continuing education and training opportunities should be provided to all data collectors, including frontline health professionals, managers, and specialists. The training should be individualized, measurable, and may focus on communication skills for data collection, and criteria and procedure of health service provision [138, 146, 147, 152, 153].

Attributes of good leadership include (1) strengthened coordination, cooperation and communication among government agencies and between healthcare facilities and health professionals; (2) recognition of the importance of data to be collected; (3) provision of sufficient funding; and (4) allocation of full-time staff or specific staff to data collection [103, 127, 135, 142, 143, 159]. Examples of good leadership include the development of a less resource-intensive approach by using strategies of decentralization to empower the management team in the field and establishing a multi-level supervision network that includes health departments and health care facilities [103, 142]. Supervisors can perform real-time field quality assurance and control activities.

Implementation of electronic systems, installation of local system infrastructure, and maintenance of a network across data collection facilities are sometimes costly; therefore, funding is critical for data collection in resource-constrained settings [130, 142]. Availability of funding can improve data quality.

## 3.4 Discussion

The quality of the data collection process is a key component of overall data quality in the PHIS [30, 31]. Conceptualization of the quality of the data collection process for PHIS is also requisite for reaching public health high data quality goals. A recent evaluation of data quality in the country health information systems by WHO in a global context has found that data management was the weakest component of the system performance [32]. A lack of knowledge about the key factors influencing the quality of the data collection process for PHIS has hindered data quality improvement and thus has impeded the effectiveness of data-driven monitoring and performance evaluation for public health programs. Effective process assessment of data collection that focuses on how data are collected will help standardize the performance of public health programs by comparing "the specific actions taken, events occurring, and human interactions with accepted standards" [44]. Prior studies have explored some factors that may affect the quality of the data collection process. But consensus on a comprehensive and systematic assessment of the process has not been reached. Identification of the essential components of the quality of data collection is needed to guide efforts in the development of a quality framework for PHIS.

The most commonly reported quality dimension for the data collection process is data collection management; half of the identified facilitators and barriers belong to this dimension. Key areas demanding an effort for improvement include the design of the data collection form, data collection practice, and data collection quality assurance. Standardization of public health data collection practice is a long-standing issue, together with the integration of different data sources and data collection systems in public health. These key study findings reflected a primary concern with the definitions and characteristics of data collection. A variety of definitions and different quality criteria of the data collection process may

contribute to a wide range of factors that affect the quality of the process.

The data collection process is recognized as a systematic process that is consisted of the interrelated and interdependent parts. However, the different parts of the process and the interaction between those parts for PHIS have not been well articulated. For example, the quality of the data collection form can contribute to data completeness and standardization and thus the use and validity of data. But the association between the quality of data collection form and data quality has not been quantified. Over-emphasis on the procedures, methods and quality control parts of data collection and simply automating data collection systems cannot solve all data quality problems [42].

Data collectors play an important role in the quality of the data collection process. Extant data quality assessment instruments have not paid sufficient attention to data collectors except for their training experience [34]. Gaps existed between actual and recommended practice even though guidelines were available to data collectors [33]. These gaps may arise from inefficient communication between data users and data collectors. Seamless translation of data users' requirements for data quality into the quality of the data collection process is an effective strategy for collecting high-quality data. We suggest more contextual analysis with an emphasis on data quality criteria to meet data users' needs.

Our study identified the data collection environment as one of the four essential components of the quality of the data collection process. Training, leadership, and funding are the building blocks of a friendly and supportive data collection environment, in addition to the other factors. These factors include whether the relationship with the data collectors "is of the utmost importance" in a data collection setting [29]. Barriers to health clients' participation in health services such as poor communication, cultural safety and a lack of transport to health facilities could also affect the volume of data available for collection. Adding the data collection environment to the essential components would better inform data quality assessment in troubleshooting the factors that affect the quality of the data collection process.

Limitations of existing measurement instruments and studies were also found. Information about data quality was not provided in a third of the studies (14 articles) [31, 126, 130, 131, 137, 139, 142, 144, 148-150, 154, 157, 158]. The majority of studies used simple descriptive or qualitative data to analyse the relationship between the factors affecting the data collection process and data quality. As the identified components were distilled from qualitative analysis of the published literature, future empirical testing and practical implementation are needed.

## 3.5 Conclusions

Acceptable data quality in the PHIS cannot be achieved without a high-quality data collection process. The identification of the essential components that contribute to the quality of the data collection process is thus vital to ensure data collection leads to high-quality data. After an extended literature review, this study has identified four-dimensional components of the quality of the data collection process for public health information systems. They are data collection management, data collector, information systems and data collection environment. With empirical testing and contextual analysis, the above identified essential

components can be used in future research and practice to develop a quality framework for measuring and improving the quality of the data collection process.

# Chapter 4 Qualitative validation of 4D components for measuring quality of the public health data collection process

## Foreword

The previous chapter identified the essential components of the quality of the PHIS data collection process and proposed a preliminary 4D framework including data collection management, data collector, information system, and data collection environment. This chapter uses an expert elicitation research approach to empirically validate the 4D framework. A total of 28 experts, including three public health administrators, fifteen public health workers, and ten health care practitioners, participated in the elicitation session. A framework qualitative data analysis approach was followed to elicit themes from interview transcripts and to compare these with the elements of the preliminary framework. Following Chapter 4, the term 'dimension' continues to represent the four essential components of the 4D framework. The modified 4D framework comprises four components, that is, data collection management, data collection environment, data collection personnel, and data collection system; 16 subcomponents, including data collection protocols, quality assurance procedures, leadership, training, funding, organizational policy, high level management, collaboration among peer organizations, perception of data collection, skills and competence, communication, staffing patterns, functions of the data collection system, integration of different data collection systems, technical support, and devices for data collection; and a set of 116 indicator statements, including 82 facilitators and 34 barriers.

This chapter is a reproduction with minor corrections of the published full paper "Validation of 4D Components for Measuring Quality of the Public Health Data Collection Process: Elicitation Study" authored by Hong Chen, Ping Yu, David Hailey, and Tingru Cui, and published in Journal of Medical Internet Research 2021;23(4): e17240. doi: 10.2196/17240.

The Table and Figure numbers, the Reference numbers and the Section numbers have been adjusted to fit within the structure of the thesis. The validated 4D framework is included as Appendix B in this thesis.

## Abstract

**Background:** Identification of the essential components of the quality of the data collection process is the starting point for designing effective data quality management strategies for public health information systems. An inductive analysis of the global literature on the quality of the public health data collection process has led to the formation of a preliminary 4D component framework, that is, data collection management, data collection personnel, data collection system, and data collection environment. It is necessary to empirically validate the framework for its use in future research and practice.

**Objective:** This study aims to obtain empirical evidence to confirm the components of the framework and, if needed, to further develop this framework.

**Methods:** Expert elicitation was used to evaluate the preliminary framework in the context of Chinese National HIV/AIDS Comprehensive Response Information Management System (CRIMS). The research processes included the development of an interview guide and data collection form, data collection, and data analysis. A total of 3 public health administrators, 15 public health workers, and 10 health care practitioners participated in the elicitation session. A framework qualitative data analysis approach and a quantitative comparative analysis were followed to elicit themes from interview transcripts and to map them to the elements of the preliminary 4D framework.

**Results:** A total of 302 codes were extracted from interview transcripts. After iterative and recursive comparison, classification, and mapping, 46 new indicators emerged; 24.8% (37/149) original indicators were deleted because of a lack of evidence support and another 28.2% (42/149) were merged. The validated 4D component framework consists of 116 indicators (82 facilitators and 34 barriers). The first component, data collection management, includes data collection protocols and quality assurance. It was measured by 41 indicators, decreased from the original 49% (73/149) to 35.3% (41/116). The second component, data collection environment, was measured by 37 indicators, increased from the original 13.4% (20/149) to 31.9% (37/116). It comprised leadership, training, funding, organizational policy, high-level management support, and collaboration among parallel organizations. The third component, data collection personnel, includes perception of data collection, skills and competence, communication, and staffing patterns. There was no change in the proportion for data collection personnel (19.5% versus 19.0%), although the number of its indictors was reduced from 29 to 22. The fourth component, data collection system, was measured using 16 indicators, with a slight decrease in percentage points from 18.1% (27/149) to 13.8% (16/116). It comprised functions, integration of different data collection systems, technical support, and data collection devices.

**Conclusions:** This expert elicitation study validated and improved the 4D framework. The framework can be useful in developing a questionnaire survey instrument for measuring the quality of the public health data collection process after validation of psychometric properties and item reduction.



**Keywords:** data quality; data collection; public health informatics; health information systems; component validation; expert elicitation

## 4.1 Introduction

### 4.1.1 Background

Public health, a data-intensive discipline, relies on high-quality data to monitor the health and well-being of the population, make appropriate policy decisions for intervention, and evaluate intervention outcomes [26, 52, 162]. After two decades of development in the design and implementation of information and communication technologies (ICTs) for national public health data management, public health information systems (PHISs) have developed into essential data repositories [1, 8, 162]. PHISs have been well integrated into many nations' health information management systems, such as those of the United States, Australia, and China [32, 43, 163, 164]. The data stored in PHISs, for example, on women's and children's health, aging population, and people living with HIV/AIDS, have enabled public health agencies to formulate evidence-based policies and plan and evaluate program performance to ensure accountability for citizens and countries [9, 32, 43, 162].

As data-driven public health management assumes data are accurate, timely, and reliable, data quality assessment needs to be continuously and rigorously conducted to ensure high-quality data in PHISs [1]. Data quality is a 3D concept that includes the quality of data, data collection process, and data use. Improving the quality of the data collection process is critical for PHIS data quality management [30]. Identification of the essential components of the quality of the PHIS data collection process is the starting point for the design of effective public health data quality management strategies [1, 32].

Through appraisal and synthesis of literature that reports the factors affecting the rigor of the PHIS data collection process, we have proposed a preliminary conceptual framework that focuses on four essential components of the quality of the process [165]. These are data collection management, data collector, information system, and data collection environment. We name them 4D components, which consist of 12 subcomponents and 149 indicators (Table 4-1). Data collection management is an administrative process by which data are acquired, validated, stored, protected, and processed [32, 33]. Its indicators include appropriate data collection methods, data entry forms, and ongoing quality assurance. At the individual level, data collection personnel (replacing *data collector*) need to have a right attitude, adequate skills, and competence for the job. They must maintain adequate communication with each other. For them to execute their tasks adequately, their organization needs to provide adequate staffing with the right skill mix [165]. A data collection system (replacing *information system*) requires different systems and elements to integrate and assist data capture, data entry, and data logging. Thus, continuous and systemic functionality and technical support are required [29]. A good data collection environment includes training, strong leadership, and funding support for data collection [51]. Given that this preliminary 4D component framework was derived from an inductive analysis of the literature, validation of the framework within a certain PHIS was needed.

Table 4-1 Original 4D components of the quality of the public health information system data collection process

| Component | Description | Subcomponent | Application to this study |
|---|---|---|---|
| Data collection management | An administrative process by which data are acquired, validated, stored, protected, and processed [32, 33]. | Data collection system;<br>Quality assurance. | Concepts were adopted except that the subcomponent *data collection system* was renamed as *data collection protocol.* |
| Data collector | A data collector is a stakeholder who collects or supplies data for the PHIS, with whom the data user should build up and nurture a relationship [165]. | Staffing pattern;<br>Skill and competence;<br>Communication;<br>Perception of data collection. | Concepts were adopted except that the component *data collector* was renamed as *data collection personnel*. |
| Information system | A combination of hardware, software, network infrastructure, and trained personnel [29]. | Functions and technical support;<br>Integration of different systems;<br>Devices. | Concepts were adopted except that the component *information system* was renamed as *data collection system* and the combined subcomponent *functions and technical support* was separated. |
| Data collection environment | The context for data collection. In a government context, a PHIS is directly responsible to legislative, regulatory, and policy directives [51]. | Training;<br>Leadership;<br>Funding. | Concepts were all adopted. |

Expert elicitation is a research method used to identify and address uncertain subjects, especially when relevant local evidence or information is incomplete [45]. This method has been widely used in public health for policy decisions to generate evidence [17, 46] to achieve various research goals, such as environmental health impact assessment [45], health technology assessment [166], and economic evaluation of health gains of antenatal care [167]. Knowledge synthesized from expert opinions can form the foundation for further research.

The main procedures for a formal expert elicitation include characterization of uncertainties, selection of

experts, elicitation of expert judgments, and possible aggregation and reporting in a temporary summary [40]. The criteria for expert selection include the following: the person should be representative of the main population of interest and he/she should have sufficient intellectual ability to provide the theoretical definitions, rank the importance of the data items, and explain a potential causal relationship between them. Expert judgments should adhere to the principles of the scientific process. These are accountability, neutrality, fairness, and the ability for empirical control [168]. A facilitator, often a trained interviewer, has *the enormous potential to reduce bias in expert elicitation* by clarifying the questions to the expert [45, 166]. A systematic elicitation session could increase the validity, transparency, and trustworthiness of research [40].

### 4.1.2 Objectives

Using an expert elicitation approach, this study aims to obtain empirical evidence to confirm the components of the 4D framework and, if needed, to further develop the framework.

## 4.2 Methods

### 4.2.1 Study setting

The study was conducted within a country-level PHIS, the Chinese HIV/AIDS Comprehensive Response Information Management System (CRIMS). Acknowledged as one of the milestones for China's HIV/AIDS response programs over the past three decades [169], the CRIMS is a web-based national AIDS information management system that was established in 2008 [8]. The system has been used for routine HIV/AIDS prevention and control data collection from hospitals and all units of Chinese Center for Disease Control and Prevention (China CDC) in 2893 counties. The data stored in the CRIMS include demographic information, case reporting, antiretroviral treatment, methadone maintenance therapy, behavioural interventions, laboratory testing, counselling, and surveillance. These real-time data can be used for decision making, monitoring and evaluating HIV/AIDS prevention and control programs in the health bureaus and CDCs at national, provincial, city and county levels [9]. Therefore, high-quality data in the system are imperative. However, prior studies found that public health professionals lacked trust in the quality of data in the CRIMS and expressed concerns over the quality of the data collection process [15-17]. This primary concern of public health professionals in China has also motivated this study.

Data management within the CRIMS includes data collection, data entry, data analysis, data assurance, and data use [10]. The personnel involved in the CRIMS data management include health administrators in health bureaus, epidemiologists and laboratory technicians in CDCs, and clinicians and data registrars in hospitals. They have accumulated rich experiences from long-term empirical work in HIV/AIDS data management and were thus appropriate experts who could provide inputs for this study.

### 4.2.2 Ethical approval

This study was approved by the Human Research Ethics Committee at the University of Wollongong and the Institutional Review Board of the National Center for AIDS/STD Control and Prevention at the China CDC. All participants gave informed written consent to participate in the study and to publish individual data.

### 4.2.3 Design of interview guide and data collection form

To ensure the validity of the study, we followed 3 broad categories of validity for qualitative research in information systems proposed by Venkatesh [20]. These are (1) design validity (e.g., descriptive validity, credibility, and transferability), (2) analytical validity (e.g., theoretical validity, dependability, consistency, and plausibility), and (3) inferential validity (e.g., interpretive validity and confirmability).

During the design phase, an interview guide was developed in consultation with 7 information system researchers at the University of Wollongong: a professor, an associate professor, a lecturer, a research assistant, and 3 PhD candidates. Two open-ended questions were suggested: “What are the components of quality of the CRIMS data collection process?” and “What are the attributes of these components?”

An item represents a component or subcomponent of the 4D component framework in reference to the literature [165]. An item weight table was developed to elicit an expert’s opinion about whether an item is a component or subcomponent of the quality of the CRIMS data collection process. To avoid bias in directing the expert to the preliminary 4D component framework, we reconstructed the testing items according to group discussions with consultant researchers. Four items that are not part of the framework but frequently identified by consultant researchers in practice were added, including parallel organization, high-level management, social factors, and organizational policy. Four items that are elements of a certain original subcomponent or component were used to represent their parental components. These were data collection form and data quality assessment strategies of the component *data collection management*, data collector’s data quality audit skills, and demographics of the component *data collection personnel*. Four original items—funding, data collection personnel’s communication, staffing pattern, and integration of different systems—were purposely excluded to test the completeness of the framework item spectrum. Each item was answered as *yes* or *no*. If the answer was *yes*, the expert was asked to rank the importance of the item for the quality of the CRIMS data collection process. The rankings ranged from 1 (the highest contribution) to 16 (the smallest contribution; Table 4-2).

The interview guide and item weight table were translated into Chinese. Three bilingual authors validated the Chinese translation. The interview guide was pilot tested for content validity and face validity with 8 Chinese public health practitioners who worked within the CRIMS. All 8 practitioners agreed with the fit of the interview questions and the item weight table for the study.

### 4.2.4 Sampling and recruitment of study participants

To ensure generalizability of the study, personnel from all administrative levels in all types of organizations with at least one of data management roles for the CRIMS were considered as potential experts. They were eligible for inclusion as experts to ensure a comprehensive capture of diverse expert opinions. Those who did not have a role in CRIMS data management were excluded.

Following the aforementioned selection criteria, we used a stratified sampling method to identify the participating organizations [21]. Representativeness was ensured by a lack of significant statistical difference in data quality among provinces [15, 16]. A total of 19 organizations were selected including 3 departments of health bureaus (1 each at the central, provincial, and county levels), 10 departments of the CDCs (1 each at the national, provincial, and city levels, and seven at the county level), and 6 hospitals (4 tertiary, 1 secondary and 1 primary).

HC was an epidemiologist who specialized in HIV/AIDS prevention and control in a provincial CDC in China. She used a convenient sampling method to recruit participants working in health bureaus and CDCs. A personalized invitation message containing a cover letter and a consent form was sent through the Chinese social media QQ to 20 potential participants. All participants agreed to participate by returning a completed consent form. Web-based interviews were arranged with 18 of them through QQ media. The other 2 withdrew quoting time constraints. Of the 18 participants, 3 were from health bureaus at the 3 different levels. The remaining 15 came from 4 tiers of the CDCs: 1 at the national level, 4 at the provincial level, 3 at the city level, and 7 at the county level.

HC recruited potential participants from 6 hospitals via direct contact with hospital management. She explained the project's purpose and research process to the relevant managers in the hospitals and sought their support in recommending eligible data management personnel to participate in the field study. Being introduced by the facility management, HC contacted the potential participant and organized an interview with the person at a designated venue and time. An interview would start only after providing written consent. Overall, 10 potential participants were recommended and completed interviews. Six came from four tertiary hospitals, three from a secondary hospital, and the other from a primary health care centre.

On average, the 28 participants had worked in public health or health services for 12 years (standard deviation (SD 7 years); and in the HIV/AIDS domain for 7 years (SD 4 years). Of the 28 participants, 16 (57%) were female; 23 (82%) were aged between 30-50 years, and the other 5 (18%) were aged under 30 years. Most participants (25/28, 89%) had multiple job roles in HIV/AIDS data management.

### 4.2.5 Interview procedure

Both telephone and face-to-face interviews were conducted. An internet voice call was made for telephone interviews with the practitioners during their work break or after hours. Face-to-face interviews were conducted at hospitals. The average duration of the interviews was 44 minutes (SD 23 minutes).

Each interview started with asking the practitioner to provide answers to the 2 open-ended questions. Answers from 3 of the first 5 practitioners were related to data quality instead of the focused topic of this study, the quality of data collection process. To clarify the research topic, the researcher started subsequent

interviews with the question, *"What do you think the differences are between data quality and quality of the CRIMS data collection process?"* A further probe clarified any emerging issues raised by the practitioners. Once information saturation was reached, that is, no further issues emerged, the interview was concluded.

After the practitioners answered all the open-ended questions, they were invited to assess the 16 items listed in the weight table (Table 4-2). The other 7 items were raised by the practitioners. The average rankings were not calculated because of the small sample size.

Table 4-2 Agreement with an item being a component or subcomponent and its importance rank for the quality of the Comprehensive Response Information Management Systems data collection process (N=28).

| **Item** | **Number agreeing with the item** | **Rank (mean score)** |
|---|---|---|
| **Data collection management** | | |
| Data collection forms | 27 | 3 (4.96) |
| Data collection management system | 22 | 9 (7.95) |
| Definition of client [a] | 1 | - |
| Data assessment strategy | 27 | 10 (7.96) |
| Pilot of data collection protocol [a] | 1 | - |
| **Data collection environment** | | |
| Leadership | 26 | 1 (3.92) |
| Training | 27 | 2 (4.33) |
| Funding [a] | 3 | - |
| Incentives for data collector and clients [a] | 1 | - |
| High-level management support in upper organizations | 22 | 12 (8.5) |
| Organizational management policy | 23 | 8 (7.72) |
| Collaboration among the parallel organizations | 23 | 14 (9.65) |
| Social factors | 16 | 16 (12.19) |
| Client cooperation [a] | 2 | - |
| **Data collection personnel** | | |
| Work attitude | 28 | 4 (5.89) |
| Competence | 28 | 5 (6.14) |
| Data quality audit skills | 28 | 7 (7.71) |
| Demographics | 17 | 15 (11.94) |
| The number of professional staff [a] | 2 | - |
| **Data collection system** | | |
| Automatic functions | 20 | 11 (8.00) |

| | | |
|---|---|---|
| Technical support | 25 | 6 (7.24) |
| Input devices | 19 | 13 (9.53) |
| Structure and operation of the system [a] | 2 | - |

Note. [a] New item elicited from the elicitation session.

### 4.2.6 Data processing and analysis

All audio recordings were transcribed verbatim. The transcripts were sent to the interviewees for confirmation, translated into English, and back translated. Qualitative data analysis was conducted in accordance with the framework analysis approach suggested by Pope et al [22]. The theoretical (thematic) framework was the 4D components of the quality of the PHIS data collection process (Table 4-1). The unit of analysis was each transcript. The data analysis was conducted in 3 steps.

*Step 1: Generating the Initial Codes*

Each transcript was thoroughly read to identify and understand the meaning of the relevant text. A concise phrase was created to summarize a sentence. For example, "Reward and punishment system, which is important for a work system…This should be put in organizational management policy" (C102) was coded as "clear reward and punishment in organizational policy". "If they (managers) understand the importance to the job (data collection), you will work easily; if they don't, it is hard" (H306) was coded as "managers should understand the importance of data collection."

After the first round of transcript encoding, 302 codes were extracted and stored in an Excel database.

*Step 2: Mapping the Codes Using the Preliminary 4D Component Framework*

All the 302 codes were compared and mapped with the original indicators and subcomponents in the preliminary 4D component framework. Three data processing strategies were used in 3 different scenarios.

Scenario 1

When a code had a similar meaning to an original subcomponent or indicator of the preliminary 4D framework, the original subcomponent or indicator remained or was further refined by merging, condensing and grouping to represent the code.

Scenario 2

When the meaning of a code was not matched by any original subcomponent or indicator in the 4D framework, a judgment was made to add the code as a new subcomponent or indicator to the framework.

Scenario 3

When no empirical data could match the meaning of a certain subcomponent or indicator in the preliminary 4D framework, the subcomponent or indicator was deleted from the framework.

Iterative and recursive coding, mapping, and classification processes were applied continuously between steps 1 and 2. The 302 codes converged to the 4D component framework; 88 were grouped into the

component data collection management, 86 into the data collection environment, 77 into the data collection personnel, and the remaining 51 into the data collection system. A total of 46 new indicators emerged from the extracted codes. Of the 149 original indicators, 37 (24.8%) were deleted because of a lack of evidence support and 42 (28.1%) were further merged with codes with similar meaning but different wording. Finally, 116 indicators, 16 subcomponents and 4 components were synthesized.

*Step 3: Interpreting the Framework*

The nature of and associations among the components, subcomponents, and indicators were further assessed by the author group. Each indicator was identified as either a facilitator or a barrier for data collection. Data and themes that had been extracted from expert elicitation were constantly compared between hospitals and CDCs with varying data collection processes and contexts, and between different data collection roles played by different experts. The data analysis outputs were triangulated and discussed within the team until a consensus was reached (Figure 4-1).

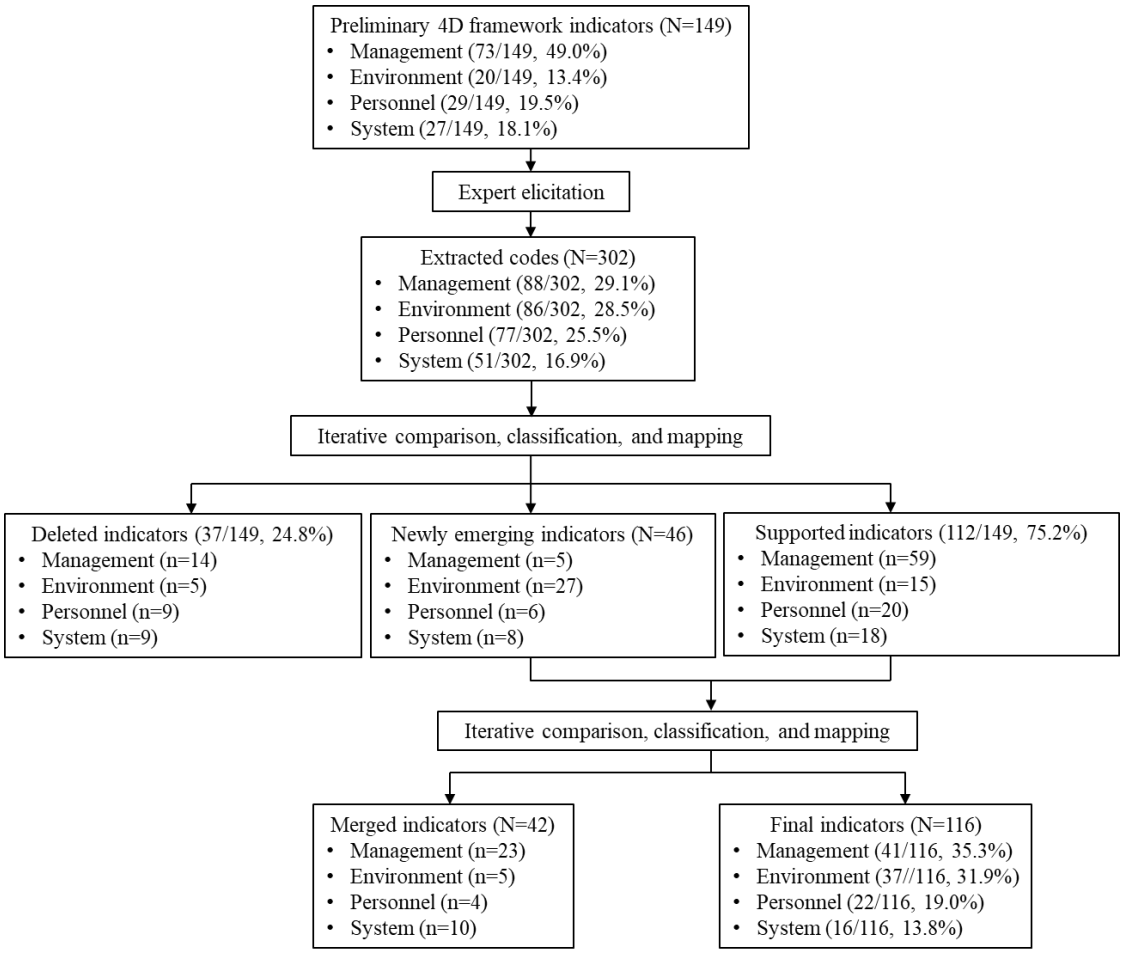


Figure 4-1 The validation process for the 4D framework.

## 4.3 Results

### 4.3.1 Overview

The 4 dimensions of the 4D framework were verified as data collection management, data collection environment, data collection personnel, and data collection system. Three new subcomponents were added: organizational policy, high-level management support, and collaboration among parallel organizations. A total of 16 subcomponents were validated and grouped into the appropriate 4D components. They were measured by 116 indicators including 82 facilitators and 34 barriers (Figure 4-2).

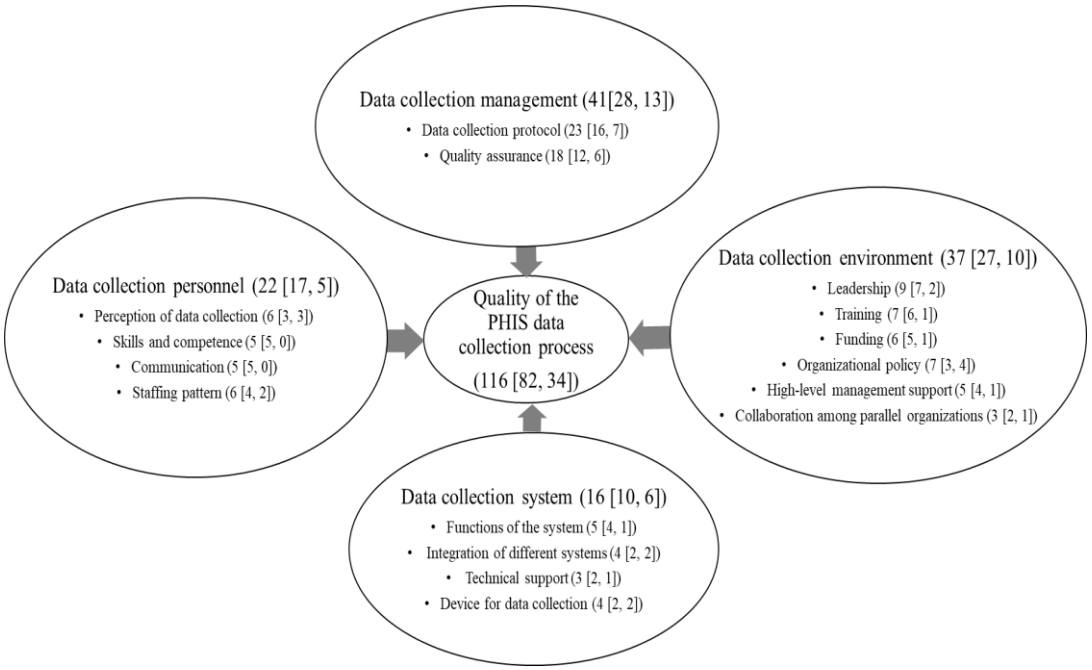


Figure 4-2 Composition of the 4D Framework.
PHIS: public health information systems.
Parenthesis: (number of indicators [number of facilitators, number of barriers]).

The next section presents the results using the 4D components to tabulate and elaborate the evidence that supports the subcomponents, and indicators of the validated 4D framework situated in the CRIMS.

### 4.3.2 Data collection management

Data collection management includes 2 essential subcomponents: *data collection protocol* and *quality assurance*. Of the 302 interview codes, 88 (29.1%) supported 59 original indicators of *data collection management*. The remaining 14 were deleted because of a lack of evidence support. Furthermore, 5 new ones emerged from the interview codes. After merging 23 supported original indicators to amalgamate similar meaning with different wording, 41 indicators, including 28 facilitators and 13 barriers, were finalized for measuring the data collection management (Appendix B Table B1).

#### 4.3.2.1 Data collection protocol

A total of 56 interview codes were related to the subcomponent *data collection protocol*. They validated

23 indicators including 16 facilitators and 7 barriers and fell under the sub-dimension of data collection form and data collection methods.

Six practitioners (C302, C303, C201, C101, C106, and A101) suggested that the data collection protocol should be aim-focused, operable, scientific, rational, and feasible for frontline data collectors. It should contain comprehensive, step-by-step guidance for the entire process of data collection (A101 and C201). The involvement of frontline data collectors in the development of a data collection protocol was an optimal practice (C302).

A total of 16 practitioners (C101, C102, C103, C104, C105, C106, C107, C201, C203, C303, C304, A101, H302, H305, H101, and H202) stressed that a data collection form needs to be clear, readable, comprehensive, and unambiguous. One of the practitioners mentioned:

> *It [Design of the form] needs to be rational to make data collection convenient and simple, and provides comprehensive data', 'should reduce data collectors burden and reduce unnecessary effort.* [C102]

To ensure that the questions about data collection are articulated in a scientific, rational, and operable manner, 3 CDC practitioners (C201, C202, and C107) recommended the following: (1) to solicit a question, one can ask questions from different angles; (2) the number of questions should be suitable and controlled within the allotted data collection time; (3) the wording of the questions including options for the multiple-choice questions must be accurate, direct, understandable, and answerable; and (4) questions should be bound within ethical considerations and should not cause harm to respondents, particularly in places where it is challenging to find confidential and private space for question elicitation.

The data collection methods should be well developed, uniform, applicable and implementable for data collectors (C302 and C301). A method is considered optimal for data collection if the task is integrated into routine data flow in a health care facility.

#### 4.3.2.2 Quality assurance

Overall, 32 interview codes were related to the subcomponent *quality assurance* and validated a total of 18 indicators, including 12 facilitators and 6 barriers. Three topics were elicited: the criteria of quality assurance, the constituency of quality assurance, and the implementation of conduct of quality assurance.

The criteria of quality assurance were consistent with the requirements of data quality, that is, accuracy, completeness, and timeliness. Therefore, quality assurance is "able to thoroughly, quickly and accurately assess data accuracy, completeness and timeliness" (C203).

Clinicians believed that data quality audits were useful in motivating data collectors because their managers may provide extra funding to incentivize this activity. H201 explained the advantage of a data audit:

> *On one side, it is useful to provide further verification guidance to our routine work, and correct deficiencies in operational procedures because we are new to this job. On the other side, if they could brief the findings to our manager, it would be even better…For example,*

*if my workplace was equipped with the needed amenities, then it will be easy and convenient. It does not necessarily need further monetary injection.* [H201]

Two health administrators (A401 and A301) who held a position at the national and provincial administration used the CRIMS data regularly for decision making. They relied on the quality of the data quality assessment conducted by all levels of CDCs. "The professionals will ensure the quality of data collection process" (A401), whereas "it is impossible to verify the situation (of data) in the front line" (A301).

A401 expressed his concern about the deliberate falsification of data, especially the *soft* data. Soft data means that its quality is difficult to assess even with field verification, such as data from high-risk population intervention, follow-up, and health education. *Hard* data are more likely to be *true*, for instance, the methadone treatment data documented on the site, and thus, *hard* data are less prone to errors:

*It does have difference in level of data accuracy. Some data are relatively accurate, such as the data about methadone treatment because they were when the patient took the medicine; that possibly would not be falsified, right? However, intervention data, the "relatively soft data", are hard to verify in the office. If you do not make an on-site verification, it is hard to control the recording of them.* [A401]

### 4.3.3 Data collection environment

The data collection environment includes 3 original subcomponents (leadership, training, and funding), and 3 newly added ones (organizational policy, high-level management support, and collaboration among parallel organizations). Of the 302 extracted codes, 86 (28.5%) were about data collection environment, with 32 relating to the 3 new subcomponents. A total of 27 new indicators emerged from these interview codes. Of the 20 original indicators, 5 were deleted because of a lack of evidence and another 5 were merged further for a similar reason. A total of 37 indicators, including 27 facilitators and 10 barriers, were finalized to measure the data collection environment (Appendix B Table B1).

#### 4.3.3.1 Leadership

Of the 28 practitioners, 26 (93%) agreed that leadership is a subcomponent of the quality of the CRIMS data collection process, ranking first among all subcomponents. Twenty-four codes were related to *leadership*. A total of 9 indicators including seven facilitators and two barriers, were validated for measuring leadership.

Concerning qualification and role, leaders should be role models with professionalism (C103, C105, C106, C203, and H304). They are **"**able to ensure the procedures to be executed up to standards, ensure the implementation of requirements and protocols of data collection, analysis, and use, and thus ensure data quality" (C203). To initiate a new task data collection, the leaders should have a clear roadmap for assigning and executing the task (A101). Leaders should have strong organizational capabilities to push it forward (H301, H303, and C106). Therefore, leaders do not necessarily have to do everything by themselves but

should be familiar with the task requirements (C103, C104, andC105). They should have the power to issue policies, clarify and assign duties and tasks, and provide financial support (C302 and C104).

The extent to which a leader attaches importance to data collection determines the quality of this task. “People follow the example of their superiors” (H304 and H305). Clinicians (H202, H203, H301, and H306) mentioned that a significant indicator of adequate notice by a leader in charge is the frequency of his/her attending the meetings or the supervision and inspection events organized by the CDC.

From the practitioners’ perspective, a good leader could “lead us well, ensuring those willing to do have the opportunity to do, and turn those reluctant to do into willing to do; this is good leadership” (H304). The management recognition of the contribution of the data collection personnel to data quality is an important motivation factor for data collectors (C102 and H305). It could be in the format of “oral praise to recognize and formal acknowledgement beyond financial incentives” (C102). As commented by H305 and H306, “our leaders all think highly of this job (data collection). Otherwise, the staff would not care.” “Data collection personnel need to be respected, trusted, acknowledged, and complemented by leaders” (H304, C104, and C302).

#### 4.3.3.2 Training

Of the 28 practitioners, 27 (93%) agreed that training is a subcomponent of the quality of the CRIMS data collection process, ranking second among all subcomponents. A total of 19 interview codes about training generated and validated 7 indicators, including 6 facilitators and 1 barrier focusing on the objective of training, and the methods to deliver it and evaluate it.

The goal of training is to equip data collectors with qualified work competence and professionalism (C102, C103, C104, C105, C106, and C302):

> *The training objective is to equip the data collectors with work competence, with good work professionalism, such as work abilities and skills.* [C302]
> *I think training is more related to communication of [data collection] skills. Firstly, we must be familiar with the survey, then we will explore how we get good data. Learning skills is an objective to be reached via training.* [C104]

Therefore, training needs to focus on the standardization and uniformity of the data collection process. These include objective, methods, and time frames for data collection (C203, C103, C104, C106, and H304). The trainees should understand the definition of data to be collected, have good knowledge about all procedures for data collection and adhere to the standardization.

Interactive training between trainers and trainees has been suggested (C103). During training, trainers should address work issues and help trainees learn what to do and how to do it (C103 and C105). Trainers should not just talk and go and be disinterested in whether the trainees understand or not. Trainers who were welcomed by trainees were those quickly responded to trainees’ questions (C105) and those providing empirical field practice examples in the training session. C103 suggested “if the trainers give more empirical examples for the training, the trainees may obtain a better understanding.”

Data collection personnel, especially the newly recruited staff, need training after recruitment and refresh their knowledge every year about what and how to do. On-the-job training, hospital webpage training, and exams have been used in health facilities (H101 and H306). Building up a training network which installs materials and sources under the circumstance of high staff turnover is recommended (C106).

Given that the training results might vary among trainers, a training assessment was recommended, including selecting trainers, training methods, and training contents. C103 claimed that the higher the level of a training organization such as international organizations and high-level CDCs, the better the training quality.

#### 4.3.3.3 Funding

Although the subcomponent funding was not included in the item weight table, 10 relevant codes emerged from the interview transcripts and generated 3 new indicators. Three original indicators remained. They gave rise to 5 facilitators and 1barrier to measuring the subcomponent funding.

From the CDC professionals' perspective, funding should support purchasing data collection devices such as computers, printers, and even vehicles (C301, C103, and C104). Funding should provide compensation, such as gifts for health clients to seek their cooperation for data collection (C103). Otherwise, "without funding support, without policy, and without competent personnel, data quality may be problematic, or even a fake product made up in office" (C103). Continuous funding support for previously funded projects is needed to avoid the situation of "when the Demonstration Project finished, funding decreased significantly" (C104).

From the hospital data registrars' perspective, HIV/AIDS work does not bring in profit, an activity that does not support the profit goal of the hospital (H301, H202, and H203):

> *HIV/AIDS prevention activities do not bring in profit, the doctors in the hospital should be committed and have spirit of dedication. However, in market economy, hospital needs profit, and is focused on pursuit of economic cost effectiveness.* [H301]
> *Without funding support, clinicians think they are volunteers for HIV/AIDS data collection. Therefore, sometimes, they are unwilling to do this job.* [H203]

Therefore, given that "funding support can provoke work" (H201) and "the cost of management and treatment can be reimbursed" (H203), "funding support for data collectors must be fully implemented" (H202 and H203). The health administrator (A101) had already recognized this need and promised to further push this agenda.

> *In another aspect, it might be related to boosting work morale to encourage them [data collection personnel] by increasing funding support. For example, they may get some subsidies for the work they are doing or have done. Currently we do have some funding. The performance-based salary system is inflexible. It may be problematic to link their income with their performance. This shortage, maybe, is what we need to tackle, for example, from*

*the perspective of national management. We should be able to do, but not much has been done yet. They should get a better income. This aspect is what we should do.* [A101]

#### 4.3.3.4 Organizational policy

Organizational policy is a new subcomponent. Of the 28 practitioners, 23 (82%) agreed to place it in the component of the data collection environment. A total of 13 codes were related to the organizational policy and generated 7 indicators, including 3 facilitators and 4 barriers. These indicators were primarily concerned with what organizational policy is desirable for HIV/AIDS data collection.

The organizational policy was critical to ensure the execution of the data collection activity (C104 and H101). "If they attach importance to the job, you will work easily; if they don't, your work is a challenge" (H306). It was regarded as more important than the actual process of data collection because the latter could be controlled by the data collector (H303). The organizational policy should "support recognition and reflection of the real situation and encourage analysis of existing issues, a proactive adaptation of scientific findings generated from analysis of high-quality data" (C203).

Desired organizational policies of the CRIMS data collection process included (1) ensuring sufficient funding, staffing and material support, for example, "as long as the workload is increased, more staff is assigned" (H101); (2) embodying good management and coordination; (3) having a built-in reward and bonus scheme (C301 and C202) to "motivate people to come to work well" (H303).

Indicators of a poor organizational policy relating to data collection included the following aspects: (1) data collection was set up as a part-time job, (2) narrow workspace insufficient for data collection (H302), (3) increased workloads without adequate payment (H201), and (4) the culture of "eating big-pot-rice" (C106).

#### 4.3.3.5 High-level management support

High-level management support was another newly added subcomponent that 79% (22/28) of the practitioners agreed to. A total of 19 interview codes generated 5 indicators, including 4 facilitators and 1 barrier, to measure this subcomponent of high-level management support.

High-level management support provides assurance (C201); assistance for training; responsibility for policymaking (H305); and being scientific, specific, and rigorous for decision making (C104 and C106). It enforces an appropriate reward and punishment mechanism (H303). High-level management support also means funding support and making essential data collection tools such as vehicles available (C103).

Conversely, high-level management support should "not impose excessive administrative pressure on data collectors because it may compromise data integrity and accuracy in data collection. The management should not affect and intervene in the data collection process and the data. Otherwise, it may cause a negative consequence of manipulating results" (C203). In practice, the policy had a significant impact on the data quality (C104 and C302). The health administrator (A301 from the provincial health bureau) had a different viewpoint: "currently, as for the HIV/AIDS epidemic data collection, indeed there is no intervening in our work, basically it (data) is reliable, no concealment."

High-level management support was recognized as “a strong power that can veto by just a couple of words” (A101 from the county health bureau). The more the emphasis on data quality placed by upper management, the more time would be invested by data collectors towards data quality and vice versa (C102). “No site auditing, no proper work” (H303). However, the more the layers between the high-level management and the frontline data collection organization, the more difficult it is for the organization to execute the data collection process (C104).

The CDCs were considered by H201, a clinician in a secondary hospital, as “supportive” high-level management. The CDCs were also expected to be of help and to understand “why, what and how” about data collection. H301, a data registrar in a tertiary hospital, suggested that the local CDC should “clarify the work-flow in hospital and do not just require us doing this and doing that without distinction.”

#### 4.3.3.6 Collaboration among parallel organizations

Collaboration among parallel organizations was a third newly added subcomponent, with 82% (23/28) practitioners agreeing. A total of 14 interview codes were related to collaboration this subcomponent, which may contribute to HIV/AIDS data collection, for example, through hospitals and CDCs. furthermore, 3 indicators, including 2 facilitators and 1 barrier, were added to the 4D framework to measure collaboration among parallel organizations.

It was found that sometimes the quality of the data collected by the collaborated organizations may have inferior quality than those collected by the CDCs, if without staff in charge. Therefore, if data to be collected were provided by a collaborating organization, C403 suggested a coordinated AIDS committee will contribute to high quality of data collection. He stressed, “If the parallel organizations with dependency in data do not have a right attitude toward data collection, or conduct data collection in a reckless manner, then the data to be collected would be worse (in quality) and useless.”

A public health professional (C203) working at a city level CDC stated the parallel organization ‘should not use vicious competition and negative approaches to intervene with public health data collection and organizations. They should cooperate, coordinate and facilitate.’

### 4.3.4 Data collection personnel

The component *data collection personnel* included 4 essential subcomponents: *perception of data collection*, *skills and competence*, *communication*, and *staffing patterns*. Of the 302 interview codes, 77 (25.5%) supported 20 of the 29 original indicators of the data collection personnel in the preliminary framework. Six new indicators emerged, and 4 were merged further. There were 22 indicators, including 17 facilitators and 5 barriers for measuring data collection personnel.

#### 4.3.4.1 Perception of data collection

All 28 practitioners agreed that data collectors’ perception of data collection is an important subcomponent determining the quality of the CRIMS data collection process. Of the 6 original indicators, 4 were supported by the interview transcripts, 1 was deleted because of a lack of evidence, and the other was merged with 2

newly added indicators. Six indicators, including 3 facilitators and 3 barriers, were finalized to measure the perception of data collection.

From some practitioners' perspectives (C102, C103, H306, H202, and H203), the CRIMS data collection process would not be as complicated if the data collection personnel were aware of its importance, which would also lead to better data quality. As H203 said*:*

> *It is a matter of how serious they (doctors) are definitely. Because this (data collection) is a very simple and easy job. If you pay attention to it, you can do it well.* [H203]

H202 and H203, 2 public health data registrars working in a secondary hospital, agreed that the priority given by clinicians and managers in the hospital could significantly improve the quality of the data collection process and thus data quality:

> *It is an issue of whether the doctors and management value it (data collection). If the management values data collection, doctors will also value the activity.* [H203]

It was suggested that the *perception of data collection* should not only be measured by receptibility to data collection but also by 2 new indicators, including commitment of the data collection personnel for data collection and their attitude to integrity (C103, C201, C203, C302, and H203). The manifestation of *good* attitude may be "data were consistent between the paper-based and the electronic records of the CRIMS" (C103). The fabrication of data or negligence is often caused by poor attitude rather than incompetence or lacking training for data collection. Burnout demotivates data collection personnel to treat the job as their job responsibility. C106, a public health professional who had 8 years of work experience at a county CDC for HIV/AIDS prevention and control, suggested that burnout may appear after working on the same job for a long period. "Now nobody values much about this job, so not many are willing to do it, including me" (C106).

#### 4.3.4.2 Skills and competence

All 28 practitioners agreed that data collection skills and work competence were important for data collection personnel. Five indicators, all facilitators, were recommended for measuring the subcomponent skills and competence. This subcomponent was a *must-have* capability for frontline data collectors (C202), which is more important than the data collector's education level (C201, C102, and C103):

> *If they [with high education degree] do not have adequate work experience, if they do not have work skills, they cannot find the solution to the problem.* [C201]

Besides the skills for data quality check, the subcomponent skills and competence includes an accurate understanding of the objective of data collection, contextual knowledge, and the definition of data items (C102, C103, C106, and H102). Data collection personnel should be able to make a rational judgement about the reliability of a data source and ensure data accuracy and completeness (C302, C202, C203, C104, C105, C106, A101, and H302). Communication, organization, coordination, and writing skills were also desired skill sets recommended by practitioners for a competence-based framework (A101, C302, C201, C102, H302, and H305).

The data collection personnel should be professional and receive training in data collection. Interns were not considered qualified for data collection and reporting. H302, a clinician from a tertiary hospital, suggested that work competence means being mature and experienced, which is not what an apprentice is up to. H301 and H306 reported that the interns in tertiary hospitals were asked to fill in the data collection forms for busy clinicians.

#### 4.3.4.3 Communication

Although communication was not listed in the item weight table, a lack of good communication among data collectors, as described in the preliminary 4D component framework with 5 facilitative indicators, was verified by the practitioners, particularly those who need to directly interact with health clients in routine work (H302, H305, H201, and C106).

H201, an HIV/AIDS specialist, felt embarrassed in detecting transmission routes through conversation with AIDS patients. She thought that transmission routes were a private issue, especially for young men. If the data to be collected do not affect treatment, then data quality can be compromised in the interest of preserving the privacy and dignity of patients:

> *All in all, it (knowing whichever transmission route) does not affect treatment. Through conversation with them, I feel these patients are worried about we, doctors, are discriminating against them. This is the major concern. So, collecting this type of data (transmission route) is neglected in my job.* [H201]

C106, a county CDC professional, felt that it was difficult to communicate with AIDS patients during follow-up:

> *Sometimes, I do not even know how to communicate with them. Like meeting someone new, I am not sure what kind of psychological characteristics the person has. Basically, I feel them difficult to deal with. I do not even know how to talk to them. Sometimes it is fine; this feeling has always been there.* [C106]

She also felt that she was not getting adequate support from her colleagues in a routine job:

> *Having been in this job so long, it is embarrassing to ask others certain problems you encounter. You can only formulate solutions by yourself. You find it difficult to ask others. Better do it yourself.* [C106]

#### 4.3.4.4 Staffing patterns

Although the staffing pattern was not in the item weight table, it was mentioned by 11 practitioners. A total of 18 interview codes supported 6 of the 7 original indicators, including 4 facilitators and 2 barriers.

Practitioners frequently mentioned a lack of an adequate number of competent public health professionals:

> *There are only two staff members assigned to work at the front line of HIV/AIDS control by the Department of AIDS. These two staff members have to collect all*

*data, they are under enormous pressure, this indicates the staffing level is inadequate.* [C103]

*I feel the most challenging is staffing level. Lots of work needs people to do. It does not mean there is no staff to do the work but almost everyone has several parallel lines of work happening at a given time. Like us, old employees, are all part time in regard to data collection.* [C107]

In C107's workplace, employment of contractors was a major approach to fill the vacancy, but it was not favoured by local public health professionals because of high turnover. The professionals even refused to train the contractors because they were worried that their efforts would be wasted if the contractors quit the job soon after the training was completed.

Experienced staff and female staff were considered (by C302, C201, C101, C106 and H302) to be the optimal personnel for collecting quality data, rather than young practitioners, because of their experience in interacting with and establishing rapport with AIDS patients. Four practitioners (C302, C105, C106, and H305) suggested that education level, training, experience, personality, and value could affect work competency and thus, the quality of data collection.

The health administrator from the national Ministry of Health (A401) suggested a need to increase the recruitment of frontline data collectors to cope with the increased workload in HIV/AIDS prevention and control.

### 4.3.5 Data collection system

The component data collection system includes 4 subcomponents: functions of the system, integration of different information systems, technical support, and devices for data collection. A total of 51 codes for this component were identified, which supported 67% (18/27) of the original indicators about the data collection system in the preliminary framework and generated 9 new indicators. After comparison, 11 original indicators were further merged. A total of 16 indicators, including 10 facilitators and 6 barriers, were developed to measure the component data collection system (Appendix B Table B1).

#### 4.3.5.1 Functions of the data collection system

A total of 17 interview codes were related to the subcomponent *functions of the data collection system.* They supported 8 original indicators of this subcomponent. Two new indicators emerged, and 5 original indicators were merged. A total of 5 indicators, including 3 facilitators and 1barrier, were finalized to measure the subcomponent functions of the data collection system.

The practitioners agreed that he functions of the CRIMS should facilitate the visualization of routinely collected data. The CRIMS system should be humane, convenient, and error-free for data collection. For example, the system should remind data collectors wherever logic errors or incompleteness appears in data entry. In H304's words, "Machine can do something for human beings."

In recognition of the effect of *smart chart* and drop-down menus, some practitioners (C202, H302, and H305) suggested that the CRIMS should provide a user-friendly interface, allowing clinicians to add descriptive free text data; visualize data; and search by keywords, such as symptoms of a disease. The system should have convenient or automatic functions, such as iPhone's one-click for all end users and should eliminate tedious extra work. The hospital practitioners were not satisfied with the CRIMS menu allowing limited details. It was inconvenient and difficult for H303 to add additional text data.

> *Some definitions are too narrow. For example, loss for follow-up could have a variety of reasons in reality, but we could not enter these data. Another example is the patient background. They may have lots of opportunistic infections without clinical symptoms; however, there are not enough options provided by the system to capture all situations*. [H303]

An information system without adequate functions may impair data quality. C301 spent nearly fifteen minutes, one-third of her interview time, to elaborate on this topic according to her work experience. Ascertain definitions of data items in the system were not in accordance with those of the data collectors, which may lead to missing data or inaccurate data collection.

#### 4.3.5.2 Integration of different information systems

The interview transcripts supported 4 of the 7 original indicators that discussed the integration of different information systems. Four indicators, 2 facilitators and 2 barriers, were clarified for measuring this subcomponent.

Although the item "integration of different information systems" was not in the weighting table, the negative effects caused by the lack of integration of data across information systems were emphasized by practitioners from hospitals (H302, H303, H304, H305, and H201). Hospital information systems are internal systems without connection to external systems via the internet. Access to the CRIMS was only available on a few authorized computers in hospitals via internet connectivity. Clinicians could not read any information from the CRIMS beyond their hospital. Repetition in reporting often happened, causing *a wasted job* that could lead to clinicians' reporting cards being "thrown into a rubbish bin" (H305). Therefore, it is a common sentiment that appropriate integration of the CRIMS with hospital information systems is needed.

In addition, 6 practitioners raised the importance of comprehensive data storage in the CRIMS information system (A101, A401, C106, H302, H303, and H305). They suggested the system should include all work functions and topics, and cover all geographic regions from village, county, city to the province and national levels. From the national health administrator's perspective (A401), the CRIMS should be such a system:

> *From the perspective of a specific case reporting system, I think, it is a very comprehensive system; maybe no other disease reporting system can be as comprehensive as it is. The AIDS (CRIMS) should be the most comprehensive one.* [A401]

#### 4.3.5.3 Technical support

A total of 12 codes identified from the transcripts discussed technical support. Two new indicators emerged and supported the original indicators in the preliminary framework. Three indicators, 2 facilitators and 1 barrier, were finalized for measuring this subcomponent.

Practitioners (C302, C202, C104, C105, and H101) stated that insufficient technical support could inhibit the quality of the CRIMS data collection process. They emphasized that technical support should also be available for data entry. Technical support differed from training. It should be available before and during data collection. Practitioners from the county CDCs (C104 and C105) recommended that technical support for data entry should include a multimedia-supported electronic network that stores frequently asked questions, allows end users to share experiences, and provides help to use the system. It should offer access to higher level support such as that from the national institutions. Technical support must be comprehensive, problem-focused, and formal.

Technical support became exceptionally critical for a data collection task assigned by high-level authority without training. Given that data collection tasks were often directly deployed by the high-level authority through issuing an official notification (C104), A101 believed a competent team leader could play a role in offering technical support.

#### 4.3.5.4 Devices for data collection

Of the 5 original indicators about devices for data collection, 4 were supported and the other was merged. A new indicator emerged and was added. Four indicators, 2 facilitators and 2 barriers, were finalized to measure the subcomponent. The compatibility of the devices used for data collection with the CRIMS data collection system was a major concern.

The practitioners suggested that data collection devices should be of good quality (C106, C104, C102, and H101), reliable, fast, and fit for surfing the internet and should neither crash nor break down (C302 and C304). Prompts, such as “the system is under maintenance” (C102), were not welcomed by practitioners. They expected that the devices could help them perform their data work even at the peak time of data entry. It should be free from traffic jam (H306, H305, C203, and C102). Regarding data backup and security, the CRIMS has specific policies requesting the duration of data storage and the frequency of data backup to mitigate the risk of data loss (H306).

## 4.4 Discussion

### 4.4.1 Principal findings

This study used the expert elicitation research method to verify a preliminary 4D component framework for measuring the quality of the PHIS data collection process in the context of the Chinese HIV/AIDS information management system, the CRIMS.

The 28 public health data management experts for the CRIMS, with varied work experience and roles in their organizations, provided insightful inputs to issues related to the quality of the data collection process. They agreed with the 4 main components derived from the literature [165]. They ranked and commented on the importance of the original subcomponents based on their perceptions of the CRIMS data collection process. The 302 codes identified from the interview transcripts supported 75.2% (112/149) of the original indicators. These results provided the basis for a validated 4D component framework that fits well with the preliminary framework.

The validated 4D component framework was an improvement on the preliminary version. New items were identified in the expert elicitation process and added to the subcomponents of the data collection environment. These were organizational policy, high-level management support, and collaboration with parallel organizations. A total of 46 new indicators were generated and integrated into the framework, showing a wide range of characteristics elicited from the specific research context.

The original indicator statements were further simplified, merged, or deleted based on the 3 data analysis scenarios. The number of indicators in the framework finally decreased from 149 to 116.

There were changes within the framework in the proportions of the indicators for the 4 main components. The proportion of the indicators of the data collection environment increased from 13.4% to 31.9%, that for data collection management decreased from 49.0% to 35.3%, and that for the data collection system decreased from 18.1% to 13.8%. There was no change in the proportion for data collection personnel (19%). The factors that affect the quality of the data collection process are multi-faceted from the practitioners' perspective.

### 4.4.2 Lessons learned

The detailed feedback from the participants provided deep insights into many issues related to the quality of the data collection process and matters that require ongoing negotiation and development to improve it.

Under data collection management, the methods and protocols with the third ranking among all subcomponents need to be well developed, uniform and implemented. Responses on quality assurance emphasized the importance and challenges of this area. In some cases, data collection protocols and quality assurance procedures were developed and issued by high-level management in public health, but frontline personnel were not involved. This might make the data collection protocol and methods not operable or unfeasible in the field. Strategies to improve data collection management should include the involvement of frontline public health data collectors, especially those in hospitals, in the design phase of data collection protocols and quality assurance procedures [126].

A friendly data collection environment is an indispensable component for a high-quality public health data collection process. Participants ranked leadership and training as the two most important items for this component. This is consistent with and corroborated by the International Standardization Organization's recommendation that the top management should "demonstrate leadership and commitment with respect to the quality management system" [37].

Various identified organizational issues complemented the subcomponent spectrum for the data collection environment. This included avoidance of data collection intruding unduly on health facilities' operation, such as routine health services in hospitals. This also included the adequacy of communication between different organizations, such as health administration and hospitals, and CDCs and hospitals, and between data collection staff and their superiors. Financial and logistical support for the data collection process appeared to be a major issue, as is the case for health care organizations in many countries [98, 126, 170, 171]. If the level of support is inadequate, or not suitably administered, data quality will deteriorate.

On the data collection personnel component, all practitioners agreed on the importance of work attitude, competence, and data audit skills. There was some variation in opinion regarding the difficulty of the data collection process. The priority placed by the management in a hospital that performs the data collection process can significantly affect performance [172]. The fabrication of data or negligence indicated a poor attitude, requiring action by managers and supervisors. *Burnout* exhibited by staff might appear after long-term work in data collection and would require remediation, especially in hospitals [172].

Work competence was considered as a *must-have* capability for frontline data collectors. In addition to data quality audit skills, there should be an understanding of the objective of data collection, and the definition of data items. Increasing the number of competent staff would, in principle, help improve the data collection quality, though a practical difficulty has been a high turnover of recruited contract staff following training [170].

The fourth component, the data collection system, is an area that is influenced by the continuing changes in the performance and availability of ICTs [173]. Functions in the system should facilitate the visualization of routinely collected data. The system should be humane on those who operate it, and be convenient and error-free for data collection [173]. An inappropriate function in the system may impair data quality. For example, if the definition of data items in the system does not reflect the reality of the work undertaken, the results will be unconvincing.

As identified in the preliminary 4D component framework, insufficient technical support inhibits the quality of the PHIS data collection process [165]. Additional features suggested by participants included storage of frequently asked questions and shared experiences, help for staff using the system, and access to higher level support such as that from national institutions. They also saw a need for the integration of the data collection system with other information systems because disconnection may result in repetitive reporting and inappropriate use of resources [8, 171].

A study contribution is that, for the first time, we confirmed that the 4D components provide a picture of the structure and operation of the HIV/AIDS data collection process in China. The findings suggested that the Chinese HIV/AIDS information management practice provided an effective validation case and enriched the field of the quality of the PHIS data collection process. Three new subcomponents—organizational policy, high-level management support, and collaboration among parallel organizations—were considered to influence the quality of China's public health data collection process. This provided evidence to clarify the effect of the data collection environment on the quality of the CRIMS data collection process. The 4D framework also advocates the involvement of relevant stakeholders in data quality

management. This provides an example to suggest the potential of using this framework for root cause analysis to investigate and identify the *real* factors behind poor data quality.

Although this study provides useful inputs to management decisions within the CRIMS and to negotiations with other parties on resources and requirements, it is reasonable to believe that the framework is also applicable to other settings, such as emerging infectious diseases surveillance [174], general health care, education, and criminal justice.

### 4.4.3 Comparison with prior work

The context of the investigation was the Chinese HIV/AIDS program. However, many of the issues identified in the 2 sources of validation, the CRIMS and China, are also echoed in other health care systems. Inadequate staff training for data collection and limited support were also reported in birth registration in the United States [145] and in antiretroviral treatment for HIV infection in South Africa [138]. Poor communication across the health care sector and between providers was found in Aboriginal cardiac rehabilitation in Australia [131]. A lack of data linkage and sharing in electronic immunization data collection systems was described in Canada [118]. Job fatigue was found in general practitioners in European countries [172]. Regarding the transferability or generalizability embedded in the findings, this validation study has achieved design validity via a well-organized and executed research process [20].

As there are few extant public health frameworks focusing on the quality of the data collection process, therefore, there is a genuine contribution that this research has made to fill a critical gap on this topic. The successful abstraction of the 4D framework components, subcomponents and indicator statements demonstrates the need for qualitative research in a problem domain without known measurement methods. Therefore, this research has taken the right method and approach given the novelty of the research topic, despite its importance in ensuring public health data quality.

### 4.4.4 Limitations

A potential limitation of this study is that a relatively small sample of experts participated in the interview which may be small for statistical probabilistic generalizability. The control strategy was to use the theoretical sampling method, including all levels and types of participating organizations, personnel roles, and experts in the CRIMS system. This eventually brought data saturation for qualitative enquiry and provided comprehensive views of the HIV/AIDS data collection process in China. Given that the purpose of this study was to use a qualitative method to validate a preliminary conceptual framework, we have achieved our aim.

Although the number of indicators was reduced from 149 to 116, these indicators need further item reduction for ease of use in large-scale public health settings. This can be achieved by conducting quantitative questionnaire surveys with public health data management personnel at all levels. This will improve the validity of the 4D component framework and allow the reduction of measurement items to a

manageable level.

## 4.5 Conclusion

This qualitative study validated 4D components for the quality of the PHIS data collection process in the context of the Chinese HIV/AIDS information management systems, the CRIMS. The findings demonstrate that data collection management, data collection environment, data collection personnel, and data collection system are key components that determine the quality of the Chinese HIV/AIDS data collection process. The 4D component framework was further modified into a new pool containing 16 subcomponents and 116 indicators. They can be further tested and judged by practitioners and researchers in future public health data quality assessment studies.

# Chapter 5 Application of a four-dimensional framework to evaluate the quality of HIV/AIDS data collection process in China

## Foreword

The previous chapter qualitatively validated the 4D framework for measuring the quality of the PHIS data collection process. This chapter applies the 4D framework to evaluate the quality of the CRIMS data collection process with field observations in 6 hospitals and interviews with 28 public health professionals who work in CRIMS data management.

This chapter is a reproduction of the manuscript 'Application of A Four-dimensional Framework to Evaluate Quality of AIDS Data Collection Process in China' authored by Hong Chen, Ping Yu, David Hailey, and Tingru Cui, and published by the International Journal of Medical Informatics 2020; 104306. https://doi.org/10.1016/j.ijmedinf.2020.104306.

The Table and Figure numbers, the Reference numbers and the Section numbers have been adjusted to fit within the structure of the thesis.

## Abstract

**Objective:** To qualitatively evaluate the quality of the data collection process used by the Chinese national HIV/AIDS data repository (CRIMS), using a four-dimensional (4D) framework. The process is vital for the acquisition of high-quality data for ending the HIV/AIDS epidemic in China.

**Methods:** The study was carried out in China from September 2014 to April 2015. Stratified convenient sampling was conducted to recruit 28 study participants including health administrators, public health professionals and clinicians. Data were collected through semi-structured interviews with the participants and from field observations in six hospitals. Content analysis was conducted following the 4D framework.

**Results:** 61 percent of the facilitators and 74 percent of the barriers of the 4D framework were identified in the CRIMS data collection process. The CRIMS achieved better-quality data collection management. The perceived gaps primarily included: an impractical data collection protocol and invalid quality assessment mechanism for the data collection management; weak leadership and unsupportive organizational policy for the data collection environment; poor communication and job fatigue for data collection personnel; and inflexibility and inaccessibility of the data collection system. Areas for improvement included: engaging frontline staff in the design of data collection protocol, standardizing quality assurance procedures, strengthening leadership, recognizing data collectors' contributions, and meeting end-users' needs for the CRIMS.

**Conclusion:** The findings generated knowledge about the quality of the CRIMS data collection process. The 4D framework has potential as an evaluation tool for decision-makers on the improvement of the public health data collection process.

**Key words:** data quality, data collection process, HIV/AIDS information management system, China, 4D Framework

## 5.1 Introduction

Data are vital for public health program decision making and intervention, for example in prevention and control of the epidemic of human immunodeficiency virus (HIV) and acquired immune deficiency syndrome (AIDS) [5, 175, 176]. To achieve the goal of ending the HIVAIDS epidemic by 2030, the Joint United Nations Programme on HIV/AIDS (UNAIDS) recommends that member countries collect, analyse and disseminate high-quality HIV/AIDS data [6]. Since the HIV/AIDS data are captured in national public health information systems (PHISs) [7, 8], the quality of the PHIS data collection process is vital for acquisition of high-quality HIV/AIDS data.

The HIV/AIDS epidemic has remained a critical public health challenge in China [3-5]. By October 2019, about 958,000 persons were recorded living with HIV/AIDS (PLWHA) nationwide. The 2018 national HIV/AIDS epidemic estimation results indicate the actual number of PLWHA ranged from 1.1 to 1.4 million by the end of 2018 and will keep growing in the near future [4, 47]. The Chinese HIV/AIDS Comprehensive Response Information Management System (CRIMS) is a national repository of data for

HIV/AIDS 'project planning, budgeting, implementation, monitoring and evaluation' [7]. The CRIMS data collection process needs to be of high quality to meet the information needs of the decision-makers on HIV/AIDS prevention and control.

The CRIMS commenced officially in 2008 as a sub-system of the China Information System for Disease Control and Prevention, which is a large-scale web-based disease surveillance system [3, 8]. A variety of electronic reporting forms have been developed for data collection and entry into the CRIMS by the Chinese Centre for Disease Control and Prevention (China CDC) [7, 8, 177]. The data sources for these forms primarily include case reporting and management, healthcare services for PLWHA, intervention services on high-risk groups, and national HIV/AIDS prevention and control program management [8, 178]. The major data producers and collectors for the system are the county CDCs and hospitals that provide public health services and interventions to the target groups [178].

In the last decade, a data-driven performance assessment scheme has been established to assess the data quality of the CRIMS [8, 9]. Implementation of the scheme has led to an improvement in quality of the reporting data in the system [9, 10]. However, certain reporting data, e.g., case demographics, case follow-up, and intervention delivery, were still inaccurate, incomplete, missing, delayed, under-reported or leaking [11-14]. The national data quality assessment of intervention in a population at high risk for HIV/AIDS between 2014 and 2018 suggested that 79.4% (70.5%-98.3%) of the data recorded in the CRIMS and in paper records were consistent. However, in 2018 four types of consistency rates dropped to 85.3%, 91.0%, 78.8%, 70.5%, respectively, all ranking lowest within the five-year span [15, 16]. A literature review of the CRIMS data management studies in peer reviewed Chinese and English electronic databases showed that 61% (37/61) of the studies focused on assessing quality of data that had been stored in the CRIMS [10]. The other studies focused on development and management of the information system or the influential factors on data collectors. Few studies identified or provided evidence on where, when, and how data quality problems occur, the causes of poor data quality, or what strategies can be implemented to improve data quality. As data quality problems often occur in the data collection process [15, 16, 32, 33], there is an urgent need to understand the factors influencing performance of the data collection process so as to generate insights on data quality management for the CRIMS.

To date, the quality of the PHIS data collection process is an under-researched area [31]. Our previous study identified that several PHIS data quality assessment methods were focused on the data collection procedures, i.e., data recording, storage and audits, and the functions of the PHIS system that facilitate or hinder data collection [29, 31, 59]. Little attention had been given to the effect of the contextual factors (organizational, personnel or environmental) on the quality of the data collection process [31]. To address this knowledge gap, we have constructed a unique four-dimensional (4D) framework based on a systematic literature review of the topic from the international literature [165]. Unlike other data quality frameworks issued by public health institutions such as the United States CDC's Guidelines for Evaluating Public Health Surveillance Systems and the CIHI Data Quality Framework [29, 32, 59], the 4D framework is specifically focused on assessing the PHIS data collection process.

An expert elicitation study to validate the structure of the 4D framework confirmed that it should cover four

dimensions (data collection management, data collection environment, data collection personnel, and data collection system) [179]. These dimensions comprised 16 subcomponents and 116 indicators including 82 facilitators and 34 barriers (Figure 5-1). By providing guidance to practitioners to harness the facilitators and to address the barriers, the 4D framework can be a promising quality improvement model to strengthen the management of public health data collection process.

In this study we applied the 4D framework to assess the quality of the CRIMS data collection process. We aimed to identify the gaps in the process and suggest improvement strategies for the HIV/AIDS data collection in China.

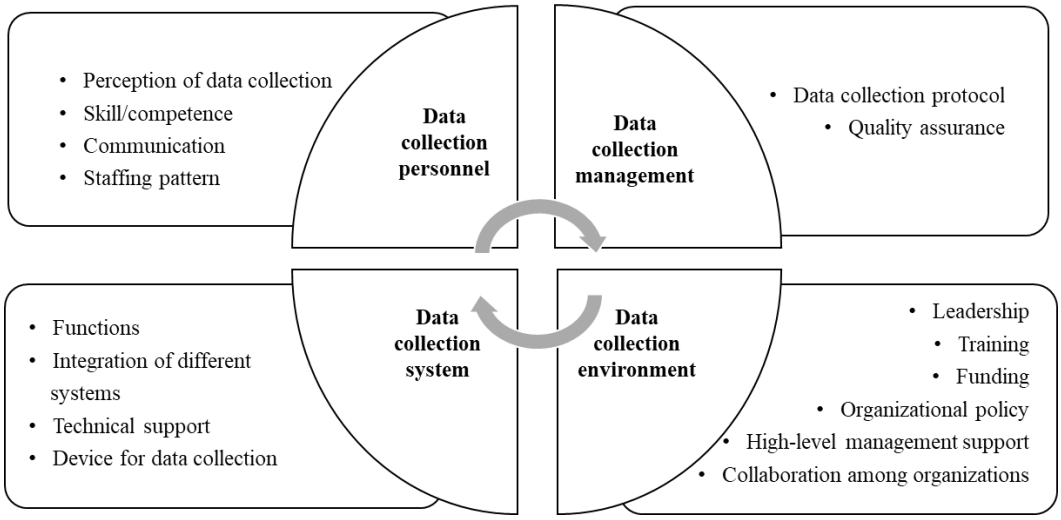


Figure 5-1 The 4D framework of quality of the public health information system data collection process

## 5.2 Material and methods

### 5.2.1 Study design and procedure

We carried out a qualitative research study in China from September 2014 to April 2015. A semi-structured interview guide was developed to focus on identification of what, where, when and how data quality problems occur in the CRIMS data collection process. The interview guide covered the perceptions, cognition, and experiences of the study participants about the HIV/AIDS data collection and quality management. The questions included 'What is your experience with the HIV/AIDS data collection process?' 'What is the quality of the CRIMS data collection?' and 'What are the factors that affect the quality of the CRIMS data collection process? Can you explain in detail?'

The interview guide was pilot tested in China among ten public health professionals to obtain their approval for the instrument validity. We selected 19 organizations as study sites using a stratified convenient sampling method. These organizations represented all administrative levels of the CRIMS including CDCs, health administration (except city level), and hospitals (Table 5-1). Eligible participants were selected from the organizations. The inclusion criteria were persons who were involved in HIV/AIDS data management

including data collection or entry, data analysis, data audit, or data use.

Health administrators and CDC professionals participated at the invitation of author HC while clinicians were recommended by the managers to HC in her visits to hospitals. An interview was only started after written consent was acquired from the interviewee. In total, thirty eligible participants were recruited; 28 of them finished interviews. The other two (both county CDC staff) withdrew due to time constraints.

To avoid interviewing employees at the workplace might make them uncomfortable to voice their opinions [30], author HC interviewed health administrators and CDC professionals via internet voice call after work. She conducted face-to-face interviews with the clinicians at a private room in the hospital. The duration of the interview was between 25 and 90 minutes. Interviews were concluded once information saturation was reached. Field observation of the HIV/AIDS data collection process was also conducted in six hospitals. HC observed the data collection activities, including filling in the reporting cards, collecting cards and data entry and examined documents related to data collection administration. During the observation, conversation to clarify relevant activities was made with the interviewee and notes were taken. Finally, the research data collected included audio recordings of the interviews and field notes taken in visits to the hospital.

Table 5-1 Characteristics of the participants

| **Characteristics** | **Health bureau (total = 3)** | **CDC (total = 15)** | **Hospital (total = 10)** | **Total = 28** |
|---|---|---|---|---|
| Coding letter | A | C | H | |
| Level of organization (coding digit) | | | | |
| National (4) | 1 | 1 | | 2 |
| Provincial (3) | 1 | 4 | Tertiary (3): 6 | 11 |
| City (2) | - | 3 | Secondary (2): 3 | 6 |
| County (1) | 1 | 7 | Primary (1): 1 | 9 |
| Gender | | | | |
| Female | - | 9 | 7 | 16 |
| Male | 3 | 6 | 3 | 12 |
| Age group | | | | |
| ≤30 | - | 4 | 1 | 5 |
| ≤40 | 1 | 7 | 7 | 14 |
| ≤50 | 2 | 3 | 2 | 8 |
| above 50 | - | 1 | - | 1 |
| Education | | | | |
| Bachelor | 12 | 8 | 1 | 21 |
| Master | 3 | 2 | 1 | 6 |
| PhD | | | 1 | 1 |
| Years of work experience (mean, standard deviation) | | | | |
| Public health/health services | 21, 1 | 12, 7 | 8, 4 | 12, 7 |
| AIDS prevention and care | 12, 4 | 7, 3 | 5, 3 | 7, 4 |
| Profession | | | | |

| | | | | |
|---|---|---|---|---|
| Public health | - | 12 | 2 | 14 |
| Clinician | - | 1 | 4 | 5 |
| Nurse | - | - | 3 | 3 |
| Laboratory technician | - | 2 | 1 | 3 |
| Public service | 3 | - | - | 3 |
| Level of profession | | | | |
| Junior | - | - | 2 | 2 |
| Middle | 3 | 13 | 7 | 23 |
| Senior | - | 2 | 1 | 3 |
| Position | | | | |
| Managerial | 2 | 7 | 5 | 14 |
| Staff member | 1 | 8 | 5 | 14 |
| Role (multiple choices) * | | | | |
| Data collection | - | 10 | 5 | 15 |
| Data entry | - | 14 | 8 | 22 |
| Data analysis | - | 16 | - | 16 |
| Data assurance | 1 | 14 | 6 | 21 |
| Data use | 3 | 15 | 1 | 19 |

Note. * A participant can undertake multiple roles in CRIMS management.

### 5.2.2 Data analysis

All the interviews were transcribed verbatim. Transcripts were sent to the interviewees for validation before being used in data analysis. Back translation was performed. Three bilingual authors, HC, PY and TC reviewed all the interview transcripts. The 4D framework was used to guide data abstraction and content analysis [22, 165]. Data analysis was conducted in four steps.

Step 1. Open coding. After familiarising herself with a transcript, HC conducted open coding of the transcript and recorded the codes in an Excel spreadsheet. As the classification of data was conducted manually, potential uncertainty was addressed through thoroughly reading through the entire transcript to understand the context, the focused topic and the logic flow from sentence to sentence. Field observation notes were coded along with the extracted codes.

Step 2. Reviewing the codes and grouping them into the indicator statements in the 4D framework. Three researchers reviewed the codes to ensure their accuracy and completeness. Then they grouped all the codes into the relevant indicator statements in the 4D framework.

Step 3. Iterative analysis and comparison of the narratives with the indicator statements in the 4D framework to achieve theoretical saturation. All the codes and the original narratives were constantly compared, and themes emerged. Each comparison result was also judged and recorded as ‘yes’ or ‘no’ respectively. ‘Yes’ means the compared indicator statement was confirmed in the CRIMS data collection process as reflected in either interview transcripts or field observations. ‘No’ means the compared indicator

was not confirmed as reflected in either interview transcripts or field observations.

Step 4. The results of analysis, including themes and indicator statements, were reviewed by all the research team members to ensure accuracy and completeness of content analysis. Guided by the 4D framework, the suggested facilitative factors served as improvement strategies to fill in the gaps for quality improvement.

## 5.3 Results

### 5.3.1 Quality of the CRIMS data collection process

Of the 116 indicator statements in the 4D framework, 75 (65%) were identified in this research. Of these, 50 were facilitators (accounting for 61% of the 82 facilitators) and 25 were barriers (74% of the 34 barriers) (Table 5-2).

The proportion of facilitators confirmed for Data Collection Environment was low at 37% (10/27); with the other dimensions the proportions identified were 68% (19/28) for Data Collection Management, 94% (12/17) for Data Collection Personnel and 90% (9/10) for Data Collection System. The proportion of barriers confirmed was low for Data Collection Management (54%, 7/13), and high for Data Collection Environment (90%, 9/10), Data Collection Personnel (80%, 4/5) and Data Collection System (83%, 5/6).

Table 5-2 Overview of quality of CRIMS data collection process mapping to the 4D framework

| **Dimension** (No. of indicators (facilitators, barriers)) | **Number observed** | **Number not observed** |
|---|---|---|
| **Data Collection Management** (41 (28, 13)) | 26 (19, 7) | 15 (9, 6) |
| Data collection protocol (23 (16, 7)) | 17 (13, 4) | 6 (3, 3) |
| Quality assurance (18 (12, 6)) | 9 (6, 3) | 9 (6, 3) |
| **Data Collection Environment** (37 (27, 10)) | 19 (10, 9) | 18 (17, 1) |
| Leadership (9 (7, 2)) | 6 (4, 2) | 3 (3, 0) |
| Training (7 (6, 1)) | 3 (3, 0) | 4 (3, 1) |
| Funding (6 (5, 1)) | 2 (1, 1) | 4 (4, 0) |
| Organizational policy (7 (3, 4)) | 4 (0, 4) | 3 (3, 0) |
| High-level management support (5 (4, 1)) | 1 (0, 1) | 4 (4, 0) |
| Collaboration among parallel organizations (3 (2, 1)) | 3 (2, 1) | 0 (0, 0) |

| | | | |
|---|---|---|---|
| **Data Collection Personnel** (22 (17, 5)) | | 16 (12, 4) | 6 (5, 1) |
| Perception of data collection (6 (3, 3)) | | 5 (3, 2) | 1 (0, 1) |
| Skill/competence (5 (5, 0)) | | 4 (4, 0) | 1 (1, 0) |
| Communication (5 (5, 0)) | | 2 (2, 0) | 3 (3, 0) |
| Staffing pattern (6 (4, 2)) | | 5 (3, 2) | 1 (1, 0) |
| **Data Collection System** (16 (10, 6)) | | 14 (9, 5) | 2 (1, 1) |
| Functions of the system (5 (4, 1)) | | 4 (3, 1) | 1 (1, 0) |
| Integration of different systems (4 (2, 2)) | | 4 (2, 2) | 0 (0, 0) |
| Technical support (3 (2, 1)) | | 3 (2, 1) | 0 (0, 0) |
| Devices for data collection (4 (2, 2)) | | 3 (2, 1) | 1 (0, 1) |
| **Total** | 116 (82, 34) | 75 (50, 25) | 41 (32, 9) |

Eleven participants evaluated the quality of the CRIMS data in their responses to a question on rating this by giving marks out of ten. Three health administrators gave an average score of 8.5. The national health administrator (A401) said, 'I scored 8 based on completeness and accuracy. Regarding data collection process, the CRIMS is complete. My concern is integrity of data. Possibly influenced by performance assessment or other factors, the original data collected at the frontline may not be accurate.' The provincial health administrator (A301) said, 'I am not confined by precision. As decision makers, we are focused on the broad and big picture. I gave it a score of 9, which is fine because the CRIMS data are absolutely useful to me.'

Six county level CDC professionals gave the CRIMS data quality an average score of 8.2. A county CDC manager (C103) said, 'I personally think the national investment in interventions is inadequate in comparison with its significant value for public health. The amount of work is a 'pyramid' (heavy at frontline), but the staffing level is a reverse shaped pyramid (few personnel at frontline). We only have the capacity to handle routine work. Data quality really needs improvement. I would give the system a score of 7 at county level, which is reasonable to me.'

The participants were confident about the quality of data they collected except two from a tertiary hospital in scoring the anti-retroviral treatment data they collected. One of these, a clinician (H301), said 'I gave the quality of AIDS data a score of 6, which is much lower than that of hospital data I collected. The reason is I do not have time to dig data from patients.' The other, a data registrar (H302), said 'If evaluating purely from the source data perspective, I would give it a score of zero. For whatever reason to change the treatment regimen, I just filled in *treatment altered in accordance with requirement*.'

### 5.3.2 The perceived gaps for HIV/AIDS data collection in China and proposed improvement strategies to address these gaps

The perceived gaps for AIDS data collection and suggested improvement strategies to address these were grouped into the 4D framework (Table 5-3). The illustrative quotes from study participants are presented in Table 5-4.

The perceived gaps in the CRIMS mapping with the 4D framework primarily included: (1) an impractical data collection protocol and invalid data quality assessment mechanism for data collection management; (2) weak leadership and unsupportive organizational policy for data collection environment; (3) poor communication and job fatigue for data collection personnel; and (4) inflexibility and inaccessibility for clinical end-users for data collection system.

Improvement strategies suggested by the interviewees to fill the gaps included: (1) engagement of frontline public health professionals in the design of the data collection protocol, and standardised quality assurance procedure; (2) strengthening leadership, high-level management, on-going training and technical support; (3) enhancement of recognition and reward of data collectors' contributions and effort; and (4) meeting clinical end-users' needs for integrated data collection systems.

Table 5-3 The perceived gaps for HIV/AIDS data collection and strategies to address these

| Main gaps | Suggested improvement strategies |
|---|---|
| **Data collection management** | |
| ✧ Impractical data collection protocol | ✓ Engaging frontline public health professionals in the design of data collection protocol |
| | ✓ Continuous improvement of the data collection protocol |
| ✧ Invalid data quality assessment mechanism | ✓ Designated unit or full-time, experienced personnel to conduct on-site audits |
| | ✓ Timely feedback with clear punishment and reward scheme |
| **Data collection environment** | |
| ✧ A lack of strong leadership | ✓ Supportive managers |
| ✧ Unsupportive organizational policy | ✓ Supportive upper-level management in terms of policy, funding and human resources |

| | |
|---|---|
| **Data collection personnel** | |
| ✧ Poor communication capability | ✓ Training and technical support |
| ✧ Job fatigue | ✓ Recognition and reward for data collector's contribution |
| **Data collection system** | |
| ✧ Inflexible, mal-functional data collection system | ✓ Data collection system meeting the needs of clinical end-users |
| ✧ Disconnected, inaccessible data collection system | |

Table 5-4 Quotes from participants on perceived gaps in the CRIMS data collection process and improvement strategies to address these

| Theme | Representative quotes |
|---|---|
| Dimension 1. Data collection management | |
| ✧ Impractical data collection protocol | 'Some questions about intervention in the questionnaire are problematic. People are not willing to answer and even refuse to answer them, particularly the sensitive questions. Sometimes if we repeated the similar questions, they (respondents) would not cooperate with us anymore. The question design needs to consider operability in the field.' (C107)<br>'I cannot remember which sex worker was interviewed and tested before. Even the owner of the brothel house could not remember. They (sex workers) migrate all the time. I cannot remember every person, every face, but the questionnaire only requires the new ones to answer.' (C107)<br>'Some patients may give false answer.' (H305) |
| ✓ Engagement of frontline public health professionals in the design of data collection protocol | 'Data collection protocol should be usable. As many data are collected by frontline staff, utility means easy for these frontline staff to understand and to execute. If the frontline staff is engaged in the design, they could understand and finish the task easily.' (C302)<br>'Some questions are too 'big' (abstract) for them (the respondents) to answer. Some colleagues would interpret the questions in |

| | | |
|---|---|---|
| | | understandable colloquial languages. However, sometimes the interpretation may not be accurate.' (C201) |
| ✓ | Continuous amendment to national disease reporting card | 'It has long been used. I feel the case reporting card is simple and clear to me.' (H306)<br>'I feel the case reporting card, especially the new version is more comprehensible than the previous version.' (H101)<br>'This form (case reporting card) is very comprehensive and there is no further suggestion from me.' (H305) |
| ✧ | Invalid data quality assessment mechanism | 'We usually conduct only one field data audit every year. Sometimes we may go with leprosy supervision organized by the health bureau.' (C107)<br>'Data like intervention and case follow-up are collected by our CDC staff, therefore we do not audit these data. We audit data such as anti-retroviral treatment, which is reported by hospitals.' (C104)<br>'Some data like intervention data are 'relatively soft'. They are hard to verify in the office. If you do not do on-site verification, it is difficult to guarantee data quality.' (A401)<br>'I primarily check whether the compulsory-reporting items in the form are comprehensive or not. I do not check data accuracy.' (H101)<br>'They (data registrars) don't check how the data were collected. They come here (the laboratory) to only trace the positive case.' (H304)<br>'Now we don't need to go to the field to check the data because all cases can be sought in the electronic health record system. I would verify the consistency of data between logbook and information system once a year. If an infectious disease case was wrongly diagnosed, it is doctor's problem. A matter of doctor's competence. I cannot do anything about it.' (H306) |
| ✓ | Designated unit or full-time, experienced professionals to do on-site audits | 'The professionals conduct quality audits to ensure the quality of the data collection process.' (A301)<br>'There should be a useful strategy to facilitate the data effectiveness of quality audits. For example, the auditors should be experienced full-time professionals who are capable of conducting standard, uniform data quality assessment.' (A401)<br>'We (data auditors) have to cooperate with clinicians who have an important role to play in data collection. If only public health |

| | | |
|---|---|---|
| | | professionals are involved, nothing can be done. They cannot complete the work.' (C204 during field observations) |
| ✓ | Timely feedback with punishment and reward scheme | 'We have a reward and punishment mechanism. That is, monetary punishment for under-reporting, between 300 and 500 Chinese Yuan a case, which is paid by the hospital departments. Whether the individual doctor is fined or else is the decision of their department managers, not us. We also reward quality case report, 5 Chinese Yuan a case. We will commend or criticize the performance at weekly meetings. A monthly statistical analysis and report is also posted on the hospital webpage. Briefing at weekly meetings and fine for bad performance has improved the quality of case reporting. Now it is rare to have poor data and we don't need to do these anymore except posters on the website.' (H306) |
| Dimension 2. Data collection environment | | |
| ✧ | A lack of strong leadership | 'The manager cares about medical treatment and knows nothing about my job, neither does the hospital administration. They thought case reporting is nothing but simple and easy.' (H203)<br>'Sometimes we have to collect data after work. If the manager does not pay adequate attention to the task, we staff would not have enthusiasm; then there might be omitted data item or delayed data entry.' (C102) |
| ✓ | Supportive managers | 'Our managers all think highly of this job. The inferior follows the superior.' (H305)<br>'Our manager could make people willing to work do well and motivate those unwilling to work to do well too.' (H304)<br>'Previously, we do not know what to do and who is in charge. Then the manager assigned the task one by one. Now everyone is clear about one's own duty.' (H303)<br>'If we have leaders from either health administration department or leaders in charge of the workplace to direct the job, it would be easy to do.' (C104)<br>'Management is most important. Work collaboratively with a fair workload allocation, everyone has own responsibility. These can only be solved by the managers.' (H303) |

| | | |
|---|---|---|
| ✓ | Training and technical support | ‘Training is needed. We provide training every year. The local CDC also requires us to do this. We post training contents on the hospital web page. All newly recruited staff must be provided with training, pass test, go through online training via hospital website.’ (H306)<br><br>‘Technical support needs to be available and accessible. When reporting a card, we need to know where and whom we can seek help.’ (H305) |
| ✧ | Unsupportive organizational policy | ‘We were paid the same before and after the implementation of the performance assessment mechanism, even though the workload was increased.’ (H201)<br><br>‘The hospital needs to compensate for extra work hours otherwise who would be willing to do this?’ (H303)<br><br>‘I hope performance assessment will be put into practice with a grounded measure. Now we seemed to go back to the ‘eating one big-pot rice’ status.’ (C106) |
| ✓ | Recognition and reward for data collector’s contribution | ‘The manger should prioritize the job. When doctor and manager both recognize the importance of this job, it will be easy to do. You must follow and respect the manager; conversely the manager should take you seriously. If you are unable to see the manager, how could you report?’ (H306)<br><br>‘If we have leaders from either the health department or leaders at the workplace to direct the job, it would be easy to do.’ (C104)<br><br>‘Although my job cannot directly bring in money (for our organization), you (the manager) should know my workload, my effort and my contribution.’ (H203)<br><br>‘We received the public health allowance for a decade; however, it was cut off this year when the performance evaluation was put in place. With the increased workload and no allowance, we do not have motivation.’ (H203) |
| ✓ | Supportive environment in terms of policy, funding, and human resources | ‘Do you know why national audit is effective? Because it is on the radar screen of the county government. The meetings are either organized by the government or by the health department with the major leaders attend.’ (H202)<br><br>‘Each year we received performance scores of supervision and audit from the CDCs or health department, but the managers do not care. The |

| | | |
|---|---|---|
| | | CDCs (need authority) to organize data collection procedure in hospital.' (H203)<br><br>'In order to provide adequate supervision and support, the local CDC needs to understand the workflow in hospital.' (H302) |
| Dimension 3. Data collection personnel | | |
| ✧ | Poor communication | 'To be honest, I feel awkward to ask patients questions about transmission route. Violation of other's privacy is embarrassing. As this answer would not affect treatment, I chose to neglect the question (by taking a guess).' (H201)<br><br>'Look, every day, you have to deal with them (patients), like follow-up. Sometimes, I do not even know how to communicate with them. Especially those new ones. I don't know what kind of psychological characteristics they have. I feel I have difficulties dealing with them. Sometimes I do not know how to talk to them. I might have a communication problem.' (C106)<br><br>'I had made good arrangement for patients, but they would not appear on time. Of course, data will be missing.' (H301) |
| ✧ | Job fatigue | 'I am always told that we are young, we have to work more, do more. I would rather not to do it even with monetary incentives.' (H302)<br><br>'The longer you worked in this area, the more you dislike this job. I feel many staff is unwilling to do this job, including me. As time passes, we would have some negative thoughts." "If you have already hated this job, then it is very difficult for you to do the job appropriately. What you can do is to tell yourself, I must be positive and dedicated. Only in this way the work can be done.' (C106)<br><br>'We are so tired, and we don't like this job, feeling like no value at all.' (H203)<br><br>'I am getting bored and bored. Because hospital performance is measured by revenue, but this job does not create any revenue. We can only try our best.' (H202) |
| Dimension 4. Data collection system | | |

| | | |
|---|---|---|
| ✧ | Inflexible data collection system | 'Some data (we) are not able to enter or extract because the system does not cover it. Therefore, lots of data were lost.' (H301)<br><br>'In patient follow-up, sometimes the doctor forgot to enter data into the system; but the system does not allow data to be entered after the completion of this entry. I think the system is not flexible to cover this situation.' (C301) |
| ✓ | Adaptable to the needs of healthcare and public health services | 'Previously when we did not have the system, if the medicine is lost or if some people made a mistake nobody knew. Now the system allows tracking and recall. You can check the stock of medicine whenever you log in the system. The speed of data analysis has also greatly increased, including the amount of data.' (H302) |
| ✧ | Disconnected, inaccessible data collection system that does allow flexible data reuse | 'The hospital information system is not connected to external systems thus we are not able to search all data. Sometimes I don't know whether the case was reported or not. This has caused repetition in case reporting, not only for infectious diseases but also for chronic diseases. What I have done including data registrar is a waste of time.' (H305)<br><br>'It is time consuming. When I see a patient, finishing the consultation means I have finished my job. But I have to fill another form, enter the same data again. With all this effort, I could not see the data myself.' (H301)<br><br>'I am glad that you are doing this (evaluating the information system and data quality). We, doctors at the coalface, have been working very hard for this information system and have contributed a lot; however, we still cannot use the system. I feel it is a great pity. It makes us feel uncomfortable and made the job hard to do. What benefits or advantages does this system provide to us? At the moment, it seems not enough for us.' (H301)<br><br>'Data reporting is simple. If the system can be more automatic and user-friendly, it would be better. For example, we do not need to conduct double data entry if the system was connected to the hospital system. Look at our hospital information system, once you click on it, if you have done the test, you would have this information. But your system (CRIMS) does not work that way.' (H303) |

Note: * Gaps are shaded, and improvement strategies are non-shaded in the table.

## 5.4 Discussion

This study evaluated the quality of the CRIMS data collection process for HIV/AIDS prevention and control in China. Through interviewing the domain experts who were directly involved with data collection and observing the clinical HIV/AIDS data collection process, the study confirmed 61% of the facilitators and 74% of the barriers from the original 4D framework. The findings might have identified the 'real' factors behind the 'dropping' consistency rates of 2018 in the CRIMS data collection process [15, 16]. As the results indicated directions and options for improvement, the framework would serve as a diagnostic tool for quality management in the CRIMS data collection process.

It is notable that Data Collection Environment had a much lower proportion of facilitators than the other three dimensions and a high proportion of barriers. This suggests that the Data Collection Environment is an immediate focal area for improvement. Although Data Collection Management attracted some adverse comments from the study participants it contained much fewer barriers than the other dimensions and many more facilitators, suggesting a reasonable level of performance and better quality.

A useful data collection protocol is essential for the success of the PHIS data collection. There are many middle layers of staff from the frontline to high-level management who are responsible for the design and dissemination of the protocol. It is important to ensure the data collection protocol is useful and easy to use in field data collection, e.g., by engaging the frontline staff in its design. The positive feedback from the clinicians on revision of disease case reporting in the CRIMS has illustrated the need for continuous improvement in the data collection protocol to ensure it is fit for use [29]. Design and implementation of systematic, structured and standardized data quality assessment methods are also important for capturing high quality data.

Weak leadership and unsupportive organizational policy were the major complaints from the frontline workers in the dimension of data collection environment. Conversely, the managers in two tertiary hospitals were complimented by their subordinates for their efforts and achievement in data collection management. These findings suggest the importance of leadership support for public health data collection, a prerequisite for many quality management system [37, 172]. Such support includes allocation of enough funding and human resources, and stipulation of a facilitative organizational data collection management policy. While some organizations do well, others need to improve their leadership support for public health data collection.

The role of frontline data collection personnel in ensuring the quality of data collection is undeniable. Barriers to the performance of the data collection personnel include job fatigue and inaccessibility to the CRIMS data. These gaps cannot be completely overcome by the data collection personnel themselves. Burnout is one of the frequently highlighted barriers to quality healthcare services. This is not unique to the public health service in China CDCs and healthcare sector [172, 180, 181]. As financial incentives alone have proven to be inadequate to solve this problem, the country leaders need to acknowledge and promote the importance of public health as an integral part of a nation's healthcare system and recognize the contribution of the public health professionals [172, 182, 183]. The frontline data collection personnel's voice needs to be heard and addressed, their contribution and efforts on PHIS data collection needs to be

acknowledged by the PHIS data users, in particular, the designers, managers and administrators.

The inflexible CRIMS data collection system and its separation from the local EHRs in hospitals have impaired the utility and usage of HIV/AIDS data for clinical end-users. Integration of different data collection systems has been a long-standing issue for healthcare systems worldwide due to the complexities of balancing clinical needs, data security and prevention of data breach [32, 182]. This study suggests the need to address the uniformity and standardization of EHR data to support public health.

### 5.4.1 Limitations of the study

The research findings were drawn from the interview responses of 28 public health domain experts who use the Chinese CRIMS system. Caution needs to be taken in generalizing the findings to other public health data collection processes, though we feel that the issues identified will be applicable to many other public health systems. However, as the CRIMS has served the largest population in the world, and the study participants represent all levels of personnel in the CRIMS, the breadth of data may mitigate the limitation.

The data classification approach followed the findings in our earlier reviews. Further refinement using concepts from other data classification systems could be considered, though our approach appears to have a clear focus on the public health setting in which the study was situated. Further appraisal of data quality and relevance through application of the data risk assessment tool (DRAT) and text analysis of interviews might be considered in future work [184].

The small number of participants may have also caused some indicators to be missed, which may explain why only 61 percent of the facilitators and 74 percent of the barriers of the 4D framework were confirmed. The confirmed indicators appear to provide a valid description of the CRIMS data collection process, but modification or addition to these may be necessary.

Further investigation about whether these indicators have any impact on the CRIMS data collection process is needed. Future research directions include an examination of how data quality related concepts are defined and interpreted by different stakeholders who have different roles (data collectors and data users) and in-depth analysis of how public health practitioners perceive the quality of the data collection process. A large-scale questionnaire survey using the indicators in the 4D framework is also needed for comprehensive evaluation of the quality of the CRIMS data collection process.

## 5.5 Conclusion

This study analysed and synthesized the China HIV/AIDS data collection management practices across all levels of healthcare organizations engaged in this process. It identified the process gaps and mapped these to the indicator statements in the 4D framework. It also provided strategies to address these gaps. The findings support a multi-dimensional approach to improve performance of the PHIS data collection process by the top level of the country's health system instead of by individual health facilities. These approaches include the design of a practical data collection protocol, strong leadership, supportive organizational policy,

recognition of public health data collection personnel contribution, and improvement of functionality and accessibility of public health data collection systems. The study demonstrates the 4D framework can be used as an evaluation tool for decision-makers on data collection process management and improvement for public health information systems. Further research can apply the 4D framework to general healthcare and to other settings such as education or criminal justice.

# Chapter 6 Conclusion

## 6.1 Introduction

This chapter summarizes the key findings of the PhD project. It starts with the research aims, objectives and questions. A summary of the answers to the four research questions is given. This is followed by a self-reflection on the contribution of this PhD project to knowledge and practice of PHIS data quality assessment and measurement of the quality of the PHIS data collection process. After considering the limitations of the study, the direction for future research is given.

## 6.2 Summary of the research findings

This PhD project is aimed at measuring the quality of the PHIS data collection process to ensure data quality for public health information systems (Section 1.2 in Chapter 1). The study aim was accomplished by achieving three research objectives: (1) review and synthesise the existing PHIS data quality assessment methods; (2) conceptualize and validate a framework to measure the quality of the PHIS data collection process; (3) use the developed framework to evaluate the data collection process for a country-level PHIS.

Four research questions have been answered to achieve the three research objectives.

Question 1. What methods and approaches are used in the assessment of data quality for PHIS?

Question 2. What are the essential components of a framework to measure the quality of the public health data collection process?

Question 3. How effective is the developed framework to evaluate the quality of the data collection process for PHIS?

Question 4. What is the quality of the data collection process for a country-level PHIS, the CRIMS?

The answer to Question 1 is covered in Chapter 2. The research adopts Karr et al's three-dimensional concept of data quality and redefines it in the context of public health information systems. The redefined three-dimensioal framework for the PHIS data quality assessment includes quality of data, quality of data collection process, and quality of data use. The framework guides a systematic review of the extant PHIS data quality assessment methods. It is found that the dimension of data is the main focus in the major PHIS data quality assessment initiatives. The data quailty assessment methods can be either quantitative or qualitative. The major quantitative methods are questionnaire surveys and data audits; whereas the common qualitative assessment methods are interviews and documentation review. The current focus of data quality assessment for PHIS is dominated by assessment of the PHIS data quality. There is a lack of attention to the quality of the PHIS data collection process and data use. This has led to inadequate knowledge and a lack of measurement framework to guide the assessment of the quality of the PHIS data collection processs and data use.

Chapter 3 provides the answer to Question 2 "What are the essential components of a framework to measure

the quality of the public health data collection process?". An extensive literature review was, again, conducted for synthesis and appraisal of the reported factors that affect the quality of the PHIS data collection process. The data analysis strategy follows Pope et al's five-stage qualitative healthcare data analysis framework. The application of this five-stage framework yields a preliminary framework for explaining the quality of the PHIS data collection process. The preliminary framework contains four dimensions covering 12 factors and 149 indicators. The first dimension, data collection management, includes data collection system and quality assurance. The second dimension, data collector, is described by staffing patterns, skills and competence, communication and attitude towards data collection. The third, information system, is assessed by function and technology support, integration of different data collection systems, and devices. The fourth dimension, data collection environment, comprises training, leadership, and funding.

Chapter 4 addresses Question 3 "How effective is the developed framework to evaluate the quality of the data collection process for PHIS?". To ensure the validity of the 4D framework, an exprt elicitation study was conducted in the context of the Chinese national HIV/AIDS information management systems, the CRIMS. Twenty-eight experts, including three public health administrators, fifteen public health workers, and ten healthcare practitioners participated in the elicitation session. A framework qualitative data analysis approach was followed to elicit themes from interview transcripts and to compare them with the elements of the 4D framework. A total of 302 codes was extracted from the interview transcripts, which verified 75.2% (112/149) of the original indicators and generated 46 new indicators. The final 4D component framework consists of 116 indicators including 82 facilitators and 34 barriers. The first component, data collection management, includes data collection protocol and quality assurance, which is measured by 41 (41/116, 35.3%) indicators. It is followed by data collection environment measured by 37 (37/116, 31.9%) indicators, which comprises leadership, training, and funding, as well as three newly added subcomponents, i.e., organizational policy, high-level management support, and collaboration among the parallel organizations. The third component, data collection personnel, is described by a perception of data collection, skill/competence, communication, and staffing patterns, which is measured by 22 (22/116, 19.0%) indicators. The fourth, data collection system, containing functions, integration of different data collection systems, technical support, and devices for data collection, is measured by 16 (16/116, 13.8%) indicators. This expert elicitation study has validated and made improvements to the 4D component framework, which can be applied by researchers and practitioners in designing and managing the public health data collection process.

Chapter 5 reports the results of a case study that applies the 4D framework to evaluated the quality of the HIV/AIDS data collection process in China to address Question 4, "What is the quality of the data collection process for for a country-level PHIS, the CRIMS?". The case study has identified 65% (75/116) of the quality indicator statements, including 61% (50/82) of the facilitators and 74% (25/34) of the barriers of the 4D framework in action. The major achievement of the CRIMS mapping to the 4D framework is better-quality Data Collection Management with a reasonable level of performance. The areas for improvement include engaging frontline staff in the design of data collection protocol, standardizing quality assurance procedures, strengthening leadership, recognizing data collectors' contributions, and meeting end users'

needs for the CRIMS.

## 6.3 Summary of the contributions of this PhD project to the field of the PHIS data quality assessment

This PhD project has made contributions in two research themes: a framework for the PHIS data quality assessment and a '4D' framework to assess the quality of the PHIS data collection process.

### 6.3.1 Contribution of a three-dimensional framework for assessing PHIS data quality

For the first time, this PhD project defines data quality for public health information systems as a three-dimensional concept: quality of data, quality of data collection process, and quality of data use. Data, data collection process, and data use are equally important dimensions for public health data quality assessment. The systematic review of extant PHIS data quality assessment methods that is guided by the three-dimensional framework for PHIS data quality assessment has revealed inattentiveness to the quality of the data collection process and data use. As the data collection process is one that directly determines the quality of data, any problems or misconduct in the process of data collection can cause data quality problems. There is a need for a paradigm shift from merely focusing on the quality of data to paying equal attention to the quality of the data collection process. Given that the quality of the PHIS data collection process is an under-researched area, the key contribution of this PhD project to public health information quality assessment is specifically in the area of that process. It fulfills the need to identify the essential components that measure the quality of the data collection process for PHIS.

### 6.3.2 Contribution of a 4D framework for assessing the quality of the PHIS data collection process

The project conceptualizes a unique 4D framework that is devoted to assessing the essential components of the quality of the PHIS data collection process (Appendix B). This framework is different from other data quality asssement frameworks that were focused on the data collection procedures, i.e., data recording, storage and audits, and the functions of the PHIS system that facilitate or hinder data collection [29, 59]. Instead, this framework takes into consideration the effect of the contextual factors, i.e., the organizational, personnel or environment factors. The 4D framework covers four aspects of the PHIS data collection process: data collection management, data collection environment, data collection personnel and data collection system. It leverages a set of indicators to measure the quality of the data collection process from multiple aspects in a comprehensive approach.

Also, this PhD project conducts the first study on the application of the 4D framework to assess the performance of the data collection process in the specific context of HIV/AIDS prevention and control in China. The empirical study has demonstrated the framework can be a diagnostic tool and a promising

quality improvement model to strengthen the management of the data collection process for public health information systems. It has made contributions to the scientfic community with an interest in PHIS data quality assessment.

## 6.4 Limitations of the study

Review of data quality assessment methods provides a snapshot of data quality management. This project referenced the PHIS data collection, process assessment and data quality measurement methods published from 2001 to 2016, including several PHIS data quality assessment frameworks published by the WHO and the United States etc. The attention to PHIS data quality management and assessment has increased since this study commenced; however the focus, to date, has been on the quality of the general data collection process. For example, the ISO 8000-61: Data Quality Management: Process Reference Model [185] provides a general reference to enhance data quality regarding process capability or organizational maturity in data quality management. Most of its adoption has been on business processes rather than in public health sectors [186]. Therefore, the 4D framework is the much needed contribution to the specific domain of public health data collectoin process.

From a methodological perspective, the study is based on use of qualitative research which is the strength and also the weakness of this study. Therefore, multiple data collection methods have been used to provide solid evidence, including extensive and systematic literature review, triangulation of data from different sources, and contrast and comparison of data collected in different phases. For example, the interview guide was pilot tested; a list of definitions of the constructs was provided before field investigation.

To enhance the research strength in the field investigation, I have kept observations, written up research diaries, and reported to supervisors to seek feedback, exchange opinions, and modify the interview strategies. The specific role of my twenty years of work experience within Chinese CDCs provides trust between the participants and me. I have kept close contact with the participants, and made a couple of visits to some study sites in a seven-year span between 2011 and 2018. Objective field observation and follow-up visits may offset the associated weakness of subjective interviews.

As for the representativeness of the study, the study participants and organizations included in this study were not randomly selected but came from a public health professional network based on my work link which is a convenient sampling method. There could be bias arising in such selection which may therefore not be representative of the entire population of the CRIMS data collection process. However, the study has recruited public health professionals working in health administrations, CDCs, and hospitals. They covered all levels in the CRIMS, including township, county, city, provincial and national levels to obtain data saturation.

The generalizabilty of the findings to other areas of public health may be limited due to the context of HIV/AIDS which is a unique infectious disease in epidemic. The study will also be limited by use of the Chinese HIV/AIDS prevention and control system which is in a unique governmental context.

## 6.5 Further research direction

At the time the entire project was completed, the corona virus disease 2019 (COVID-19) outbreak was reported in Wuhan, China [188, 189]. The Chinese Information System for Disease Control and Prevention, the world's largest web-based disease surveillance system came into the spotlight and was under international scrutiny. Given that the 4D framework has been applied to assessing the quality of the HIV/AIDS data collection process in China, which has successfully distinguished the CRIMS achievements, gaps and improvement strategies for further enhancement of the data collection process, it is helpful to apply the 4D framework to investigate the COVID-19 data collection process.

Future research is also required to examine the definitions and interpretations of the PHIS data quality related concepts by various stakeholders who have different roles (data collectors and data users) in the PHIS data collection and management process. It will also be helpful to conduct in-depth analysis of the various perceptions of the public health practitioners towards the quality of the PHIS data and the quality of the PHIS data collection process. A large-scale questionnaire survey using the indicators in the 4D framework is also needed to develop and validate a quantitative questionnaire survey method for the comprehensive evaluation of the quality of the PHIS data collection process. Further research can also apply the 4D framework to general healthcare and to other settings such as education or criminal justice.

## 6.6 Conclusion

After the identification of a gap in assessing the quality of the PHIS data collection process, this PhD project has focused on identification of the essential components of quality for the PHIS data collection process, an essential dimension of PHIS data quality. It contributes a three-dimensional framwork for PHIS data quality assessment including quality of data, quality of data collection process and quaity of data use. The project develops a 4D framework to assess the quality of the data collection process from four aspects, including data collection management, data collection environment, data collection personnel, and data collection system. The data collection management includes the subcomponents of data collection protocol and quality assurance, and 35.3% (41/116)of the quality indicator statements. The data collection environment consists of six subcomponents: leadership, training, funding, organizational policy, high-level management support and collaboration among the parallel organizations. It includes 31.9% (37/116) of the quality indicator statements. The data collection personnel has four subcomponents: a perception of data collection, skill/competence, communication, and staffing pattern. It includes 19.0% (22/116) of the quality indicator statements. The data collection system has four subcomponents: functions, integration of data collection systems, technical support, and devices for data collection. It includes 13.8% (27/116) of the quality indicator statements. The 116 quality indicator statements are classified into 82 facilitators and 34 barriers according to their direction of influence, positive or negative, on the quality of the PHIS data collection process.

The 4D framework has been applied to evaluate the quality of the China's HIV/AIDS data collection process, as well as being validated in this application in practice.

# Bibliography


1. World Health Organization, *Data quality review: a toolkit for facility data quality assessment. Module 1. Framework and metrics*. 2017, Geneva: World Health Organization. 5-12.
2. World Health Organization, *Monitoring results with health facility information systems: A technical consultation*. 2014, World Health Organization: Geneva Switzerland.
3. Liu, Z., et al., *Changing epidemiological patterns of HIV and AIDS in China in the post-SARS era identified by the nationwide surveillance system.* BMC Infectious Diseases, 2018. **18**(1): 700
4. Lyu, F. and Chen, F., *National HIV/AIDS epidemic estimation and interpretation in China.* Chinese Journal of Epidemiology, 2019. **40**(10): 1191-1196
5. Wu, Z., *HIV/AIDS in China : Beyond the Numbers*. 2017, Singapore, SINGAPORE: Springer.
6. Joint United Nations Programme on HIV/AIDS (UNAIDS). *Data*. 2019 [cited 2019 19 November]; Available from: https://www.unaids.org/en/topic/data.
7. Wu, Z., et al., *The integration of multiple HIV/AIDS projects into a coordinated national programme in China*. World Health Organization. Bulletin of the World Health Organization, 2011. **89**(3): 227-33
8. Mao, Y., et al., *Development of a unified web-based national HIV/AIDS information system in China.* Int J Epidemiol, 2010. **39**(suppl 2): ii79-ii89.PMID:21113041
9. Liu, Y., et al., *Quantitatively monitoring AIDS policy implementation in China.* Int. J. Epidemiol, 2010. **39**(suppl 2): ii90-ii96
10. Chen, H., et al., *Data Quality of the Chinese National AIDS Information System: A Critical Review.* Studies In Health Technology And Informatics, 2017. **245**: 1352
11. Han, J., et al., *Analysis of national data quality assessment for follow up of HIV/AIDS cases between 2009 and 2013.* Chin J Prev Med, 2014. **48**(12): 1104-1106
12. Qin, Q., et al., *Evaluation of AIDS network direct reporting quality and related indicators in China, 2010.* Disease Surveillance, 2012. **27**(12): 1007-1012
13. Hui, X.-q., et al., *Evaluation on the data quality of HIV screening project in AIDS demonstration area of Henan Province.* Chin J Dis Control Prev, 2016. **20**(6): 548-550, 554
14. He, Y. and Fu, R., *Security of 275 AIDS patient information leaking.* China Economic Weekly, 2016. **30**: 79-81
15. Li, L., et al., *Quality of network direct reporting of information about intervention service in population at high risk for mV infection in China，2013-2014* Chin J Epidemiol, 2017. **38**(9): 1197-1200
16. Li, L., et al., *Assessment of data quality of intervention in population at high risk for HIV/AIDS in China, 2014-2018.* Chin J Epidemiol, 2020. **41**(1): 85-89
17. Chen, H., Yu, P., and Wang, N. *Do we have the reliable data? An exploration of data quality for AIDS information system in China*. Studies in Health Technology and Informatics 2013 [cited 192; 1042]. Available from: www.ncbi.nlm.nih.gov/pubmed/23920816
18. Aveyard, H., *Doing a literature review in health and social care: a practical guide*. 2nd ed. 2010: Maidenhead: McGraw-Hill/Open University Press.
19. Critical Appraisal Skills Programme. *CASP checklist*. 2017 [cited 2017 February 12]; Available from: http://www.casp-uk.net/casp-tools-checklists.
20. Venkatesh, V.S.A.B.H., *Bridging the qualitative-quantitative divide: Guidelines for conducting mixted methods research in information systems.* MIS Quarterly, 2013. **37**(1): 21-54
21. Zhang, Y., Yu, P., and Shen, J., *The benefits of introducing electronic health records in residential aged care facilities: A multiple case study.* International Journal of Medical Informatics, 2012. **81**(10): 690-704
22. Pope, C., Ziebland, S., and Mays, N., *Analysing qualitative data.* British Med J, 2000. **320**(320): 114-116
23. Institute of Medicine, S., *Future of Public Health*. 1988, Washington, DC, USA: National Academies Press.
24. Andresen, E. and Bouldin, E.D., *Public Health Foundations : Concepts and Practices*. 2010, Hoboken, NJ, USA: Jossey-Bass.
25. World Health Organization, *Framework and Standards for Country Health Information Systems* 2008, Geneva, Switzerland: World Health Organization.
26. World Health Organization, *Monitoring the Building Blocks of Health System: A Handbook of Indicators and Their Measurement Strategies*. 2010, Geneva, Switzerland: World Health Organization.

27. Chan, M., et al., *Meeting the Demand for Results and Accountability: A Call for Action on Health Data from Eight Global Health Agencies.* PLoS Med, 2010. **7**(1): e1000223
28. MEASURE Evaluation. *Data Quality Audit Tool Guidelines for Implementation*. 2008 [cited 2013 30 August]; Available from: http://www.cpc.unc.edu/measure/publications/ms-08-29?searchterm=data+quality+audit OR http://www.theglobalfund.org/en/me/documents/dataquality/.
29. Canadian Institute for Health Information. *The CIHI data quality framework 2009*. 2009 [cited 2020 16 July]; Available from: https://www.cihi.ca/sites/default/files/data_quality_framework_2009_en_0.pdf.
30. Karr, A., Sanil, A., and Banks, D., *Data quality: a statistical perspective.* Stat Methodol, 2006. **3**(2): 137-173
31. Chen, H., et al., *A review of data quality assessment methods for public health information systems.* Int J Environ Res Public Health, 2014. **11**(5): 5170-5207
32. United States Agency for International Development (USAID)/MEASURE Evaluation, *Guidelines for data management standards in routine health information systems*. 2015.
33. Australian Institute of Health and Welfare, *The nKPI data collection: data quality issues working paper 2012–2014*. Vol. Cat. no. IHW 153. 2015, Canberra: AIHW.
34. World Health Organization, *Data quality review: a toolkit for facility data quality assessment. Module 3. Data verification and system assessment*. Vol. Licence: CC BY-NC-SA 3.0 IGO. 2017, Geneva: World Health Organization.
35. US National Library of Medicine National Institutes of Health. *Data collection*. [cited 2017 28 October]; Available from: https://www.ncbi.nlm.nih.gov/mesh/?term=data+collection.
36. Office of Research Integrity. *Responsible conduct in data management*. 2005 [cited 2017 18 April]; Available from: https://ori.hhs.gov/education/products/n_illinois_u/datamanagement/dctopic.html.
37. International Organization for Standardization (ISO), *ISO 9001: 2015 Quality management systems - requirements*. 2015, Geneva: International Organization for Standardization (ISO).
38. Batini, C., et al., *Methodologies for data quality assessment and improvement.* ACM Comput. Surv., 2009. **41**(3): 1-52
39. Kamper-Jørgensen, F., *Public health information systems — and EUPHIX.* Scandinavian Journal of Public Health, 2008. **36**(7): 673-675
40. Heisey-Grove, D., et al., *Using electronic clinical quality measure reporting for public health surveillance.* MMWR. Morbidity And Mortality Weekly Report, 2015. **64**(16): 439-442
41. Aqil, A., Lippeveld, T., and Hozumi, D., *PRISM framework: a paradigm shift for designing, strengthening and evaluating routine health information systems.* Health Policy Plan, 2009. **24**(3): 217-228.PMCID: PMC2670976
42. Carney, T.J. and Weber, D.J., *Public health intelligence: learning from the Ebola crisis.* American Journal of Public Health, 2015. **105**(9): 1740-1744
43. Davis, J., Morgans, A., and Burgess, S., *Information management in the Australian aged care setting: an integrative review.* Health Information Management Journal, 2017. **46**(1): 3-14.27105477
44. National Center for Biotechnology Information US National Library of Medicine. *Process assessment*. 1992; Available from: https://www.ncbi.nlm.nih.gov/mesh/68017064.
45. Knol, A.B., et al., *The use of expert elicitation in environmental health impact assessment: a seven step procedure.* Environmental Health, 2010. **9**(1): 1-16
46. Mokkink, Lidwine B., et al., *COSMIN checklist manual 2012*. 2012.
47. He, N., *Emerging changes and characteristics of the HIV epidemic in China.* Shanghai Journal of Preventive Medicine, 2019. **31**(12): 1-6
48. Winslow, C.E., *The untilled fields of public health.* Science (New York, N.Y.), 1920. **51**(1306): 23-33
49. Walker, R., *Health information and public health.* Health Information Management Journal, 2008. **37**(3): 4-5
50. Australian Institute of Health and Welfare (AIHW) National Public Health Information Working Group, *National Public Health Information Plan 2005*. 2005, Canberra: AIHW.
51. O'Carroll, P.W., et al., *Public health informatics and information systems*. Health Informatics (formerly Computers in Health Care), ed. K. Hannah and M.J. Ball. 2003, New York, NY: Springer Science & Business Media Inc.
52. Lin, V., et al., *Public Health Practice in Australia: The Organised Effort*. 2007, Crows Nest, N.S.W.: Allen & Unwin.

53. World Health Organization. *An introduction to the World Health Organization*. 2007 [cited 2013 30 August]; Available from: http://www.who.int/about/brochure_en.pdf.
54. European Commission. *European Core Health Indicators*. 2013 [cited 2013 30 August]; Available from: http://ec.europa.eu/health/indicators/echi/index_en.htm.
55. U.S. Department of Health and Human Services. *Healthypeople.gov*. 2013 [cited 2013 30 August]; Available from: http://www.healthypeople.gov/2020/about/default.aspx.
56. Preventative Health Taskforce. *Australia: the healthiest country by 2020*. 2013 [cited 2013 30 August]; Available from: http://www.preventativehealth.org.au/internet/preventativehealth/publishing.nsf/Content/nphs-overview-toc.
57. National Health and Family Planning Commission of the People's Republic of China. *Healthy China 2020*. 2013 [cited 2013 30 August]; Available from: http://www.moh.gov.cn/wsb/pzcjd/201208/55651.shtml.
58. Yasnoff, W., et al., *Public health informatics: improving and transforming public health in the information age.* Journal of Public Health Management Practice, 2000. **6**: 67-75
59. CDC, *Updated guidelines for evaluating surveillance systems: recommendations from the guidelines working group.* Morbidity and Mortality Weekly Report, 2001. **50**(RR-13): 1-35
60. Loonsk, J.W., et al., *The Public Health Information Network (PHIN) Preparedness Initiative.* Journal of the American Medical Informatics Association, 2006. **13**(1): 1-4.PMC1380188
61. Thacker, S.B. and Stroup, D.F., *Future directions for comprehensive public health surveillance and health information systems in the United States.* American Journal of Epidemiology, 1994. **140**(5): 383-397
62. Araujo, J., et al., *The profession of public health informatics: Still emerging?* International Journal of Medical Informatics, 2009. **78**(6): 375-385
63. Wang, L., et al., *Emergence and control of infectious diseases in China.* The Lancet, 2008. **372**(9649): 1598-1605
64. Demlo, L.K. and Gentleman, J.F., *Morbidity Data*, in *Public Health Informatics and Information Systems*, P.W. O'Carroll, et al., Editors. 2003, Springer Science+Business Media.Inc.: New York, NY, USA. p. 286-315.
65. Venkatarao, E., et al., *Monitoring data quality in syndromic surveillance: Learnings from a resource limited setting.* Journal of Global Infectious Diseases, 2012. **4**(2): 120-127
66. Cheng, P., et al., *The risk and consequences of clinical miscoding due to inadequate medical documentation: a case study of the impact on health services funding.* Health Information Management Journal, 2009. **38**(1): 35-46
67. Chen, H., Yu, P., and Wang, N., *Do we have the reliable data? An exploration of data quality for AIDS information system in China.* Studies in health technology and informatics, 2012. **192**: 1042-1042
68. Wilkinson, D.L. and McCarthy, M., *Use of comparative data for integrated cancer services.* BMC Health Services Research, 2007. **7**: 204
69. Qazi, M.S. and Ali, M., *Health Management Information System utilization in Pakistan: challenges, pitfalls and the way forward.* Bioscience Trends, 2011. **5**(6): 245-254
70. Rugg, D., et al., *Are We on Course for Reporting on the Millennium Development Goals in 2015?* JAIDS Journal of Acquired Immune Deficiency Syndromes, 2009. **52**: S69-S76 10.1097/QAI.0b013e3181baec7c
71. Chan, M., *From new estimates to better data.* The Lancet, 2012. **380**(9859): 2054
72. Institute of Medicine, *The Future of the Public's Health in the 21st Century*. 2003: The National Academies Press.
73. Snee, N.L. and McCormick, K.A., *The case for integrating public health informatics networks.* Engineering in Medicine and Biology Magazine, IEEE, 2004. **23**(1): 81-88
74. Wang, R.W. and Strong, D.M., *Beyond Accuracy: What Data Quality Means to Data Consumers.* Journal of Management Information Systems, 1996. **12**(4): 5-33
75. Pipino, L., et al., *Developing Measurement Scales for Data-quality Dimensions*, in *Information Quality*, R.Y. Wang, E.M. Pierce, and S.E. Madnick, Editors. 2005, M.E. Sharpe, Inc.: Armonk, NY, USA. p. 37-51.
76. Redman, T.C., *Measuring Data Accuracy A Framework and Review*, in *Information Quality*, R.Y. Wang, E.M. Pierce, and S.E. Madnick, Editors. 2005, M.E. Sharpe, Inc.: Armonk, NY, USA. p. 21-36.
77. MEASURE Evaluation. *Routine Data Quality Assessment Tool (RDQA): Guidelines for Implementation for HIV, TB, & Malaria Programs*. 2008 [cited 2013 30 August ]; Available

from: http://www.theglobalfund.org/en/me/documents/dataquality/.
78. MEASURE Evaluation. *PRISM: Performance of Routine Information System Management*. 2010 [cited 2015 April 18 ]; Available from: www.cpc.unc.edu/measure/tools/monitoring-evaluation-systems/prism.
79. World Health Organization, *The Immunization Data Quality Audit (DQA) Procedure*. 2003, Geneva, Switzerland: World Health Organization.
80. World Health Organization, *The Immunization Data Quality Self-assessment (DQS) Tool*. 2005, Geneva, Switzerland: World Health Organization.
81. World Health Organization. *Guide to the Health Facility Data Quality Report Card*. 2013 [cited 2013 30 August]; Available from: http://www.who.int.ezproxy.uow.edu.au/healthinfo/topics_standards_tools_data_quality_analysis/en/.
82. World Health Organization. *Assessing the National Health Information System: An Assessment Tool Version 4.00*. 2008; Available from: www.who.int/healthmetrics/tools/Version_4.00_Assessment_Tool3.pdf.
83. MEASURE Evaluation, *Data Quality Audit Tool: Guidelines for Implementation*. 2008.
84. Van Hest, N.A.H., et al., *Record-linkage and capture-recapture analysis to estimate the incidence and completeness of reporting of tuberculosis in England 1999-2002.* Epidemiology and Infection, 2008. **136**(12): 1606-1616
85. Savas, L., et al., *Mortality ascertainment of women veterans: a comparison of sources of vital status information, 1979-2002.* Med Care., 2009. **47**(1): 125-8.PMID: 19106741
86. Mate, K.S., et al., *Challenges for routine health system data management in a large public programme to prevent mother-to-child HIV transmission in South Africa.* PLoS ONE, 2009. **4**(5)
87. Makombe, S.D., et al., *Assessing the quality of data aggregated by antiretroviral treatment clinics in Malawi.* Bull World Health Organ., 2008. **86**(4): 310–314.PMC2647428
88. Frizzelle, B.G., et al., *The importance of accurate road data for spatial applications in public health: Customizing a road network.* International Journal of Health Geographics, 2009. **8**(1)
89. Freestone, D., Williamson, D., and Wollersheim, D., *Geocoding coronial data: Tools and techniques to improve data quality.* HIM J, 2012. **41**(3): 4-12
90. Ford, J., et al., *Using hospital discharge data for determining neonatal morbidity and mortality: a validation study.* BMC Health Serv Res., 2007. **20**(7): 188
91. Dixon, B.E., McGowan, J.J., and Grannis, S.J. *Electronic laboratory data quality and the value of a health information exchange to support public health reporting processes*. in *AMIA ... Annual Symposium proceedings*. 2011. American Medical Informatics Association.
92. Corriols, M., et al., *The Nicaraguan pesticide poisoning register: constant underreporting.* International Journal of Health Services, 2008. **38**(4): 773-787
93. Clayton, H.B., et al., *The florida investigation of primary late preterm and cesarean delivery: The accuracy of the birth certificate and hospital discharge records.* Maternal and Child Health Journal, 2013. **17**(5): 869-878
94. Chiba, Y., Oguttu, M.A., and Nakayama, T., *Quantitative and qualitative verification of data quality in the childbirth registers of two rural district hospitals in Western Kenya.* Midwifery, 2012. **28**(3): 329-339
95. Bosch-Capblanch, X., et al., *Accuracy and quality of immunization information systems in forty-one low income countries.* Trop Med Int Health, 2009. **14**(1): 2-10
96. Ancker, J.S., et al. *Root causes underlying challenges to secondary use of data*. in *AMIA Annu Symp Proc*. 2011. American Medical Informatics Association.
97. Ronveaux, O., et al., *The immunization data quality audit: verifying the quality and consistency of immunization monitoring systems.* Bull World Health Organ., 2005. **83**(7): 503-10
98. Hahn, D., Wanjala, P., and Marx, M., *Where is information quality lost at clinical level? A mixed-method study on information systems and data quality in three urban Kenyan ANC clinics.* Glob Health Action, 2013. **6**: 21424
99. Saeed, K.M.I., Bano, R., and Asghar, R.J., *Evaluation of the national tuberculosis surveillance system in Afghanistan.* Eastern Mediterranean Health Journal, 2013. **19**(2): 200-207
100. Petter, S. and Fruhling, A., *Evaluating the success of an emergency response medical information system.* International Journal of Medical Informatics, 2011. **80**(7): 480-489
101. Lowrance, D., et al., *Assessment of a national monitoring and evaluation system for rapid expansion of antiretroviral treatment in Malawi.* Tropical Medicine & International Health, 2007. **12**(3): 377-381
102. Litow, F. and Krahl, P., *Public Health Potential of a Disability Tracking System: Analysis of*

*U.S. Navy and Marine Corps Physical Evaluation Boards 2005-2006.* Military Medicine, 2007. **172**(12): 1270-4
103. Lin, W., et al., *Is the HIV sentinel surveillance system adequate in China? Findings from an evaluation of the national HIV sentinel surveillance system.* Western Pac Surveill Response J, 2012. **3**(4): 78-85
104. Harper, S.L., et al., *Improving Aboriginal health data capture: evidence from a health registry evaluation.* Epidemiology and Infection, 2011. **139**(11): 1774-1783
105. Forster, M., et al., *Electronic medical record systems, data quality and loss to follow-up: Survey of antiretroviral therapy programmes in resource-limited settings.* Bulletin of the World Health Organization, 2008. **86**(12): 939-947
106. Edmond, M., Wong, C., and Chuang, S.K., *Evaluation of sentinel surveillance system for monitoring hand, foot and mouth disease in Hong Kong.* Public Health, 2011. **125**(11): 777-783
107. Dai, L., et al., *Birth defects surveillance in China.* World Journal of Pediatrics, 2011. **7**(4): 302-310
108. Iguiniz-Romero, R. and Palomino, N., *Data do count! Collection and use of maternal mortality data in Peru, 1990-2005, and improvements since 2005.* Reproductive Health Matters, 2012. **20**(39): 174-184
109. Matheson, A.I., et al., *Implementation and expansion of an electronic medical record for HIV care and treatment in Haiti: An assessment of system use and the impact of large-scale disruptions.* International Journal of Medical Informatics, 2012. **81**(4): 244-256
110. Pereira, J.A., et al., *Exploring the feasibility of integrating barcode scanning technology into vaccine inventory recording in seasonal influenza vaccination clinics.* Vaccine, 2012. **30**(4): 794-802
111. Hills, R.A., et al. *Timeliness and data element completeness of immunization data in Washington State in 2010: a comparison of data exchange methods*. in *AMIA ... Annual Symposium proceedings*. 2012. American Medical Informatics Association.
112. Lash, R.R., et al., *Effects of georeferencing effort on mapping monkeypox case distributions and transmission risk.* International Journal of Health Geographics, 2012. **11**
113. Wang, R.Y. and Strong, D.M., *Beyond accuracy: What data quality means to data consumers.* Journal of Management Information Systems, 1996. **12**(4): 5-5
114. Wand, Y. and Wang, R.Y., *Anchoring data quality dimensions in ontological foundations.* Commun. ACM, 1996. **39**(11): 86-95
115. World Health Organization, *Country health information systems: a review of the current situation and trends*. 2011, Geneva: World Health Organization. 3-10.
116. World Health Organization, *Monitoring the building blocks of health system, a handbook of indicators and their measurement strategies*. 2010, Geneva: World Health Organization.
117. Australian Institute of Health and Welfare. *Data governance framework*. 2014 24 October 2017]; Available from: https://www.aihw.gov.au/getmedia/a10b8148-ef65-4c37-945a-bb3effaa96e3/AIHW-data-governance-framework.pdf.aspx.
118. Heidebrecht, C.L., *Electronic immunization data collection systems: application of an evaluation framework.* BMC Med Inform Decis Mak, 2014. **14**(1): 5
119. Yasnoff, W.A., et al., *Public health informatics: improving and transforming public health in the information age.* Journal of public health management and practice : JPHMP, 2000. **6**(6): 67-75
120. von Bertalanffy, L., *An outline of general system theory.* Emergence: Complexity & Organization, 2008. **10**(2): 103-123
121. Abernethy, N.F., DeRimer, K., and Small, P.M., *Methods to identify standard data elements in clinical and public health forms.* AMIA Annu Symp Proc, 2011. **2011**: 19-27
122. Ahanhanzo, G.Y., et al., *Factors associated with data quality in the routine health information system of Benin.* Archives of public health = Archives belges de santé publique, 2014. **72**(1)
123. Aidara, A.W., et al., *Quality of data gathered with International Caries Detection and Assessment System (ICDAS) assessment and dentists' perceptions of completion of dental records Quality of data gathered with ICDAS assessment.* Int Dent J, 2011. **61**(6): 314-320
124. Amouzou, A., et al., *Monitoring child mortality through community health worker reporting of births and deaths in Malawi: Validation against a household mortality survey.* PLoS ONE, 2014. **9**(2)
125. Anderka, M., et al., *Development and implementation of the first national data quality standards for population-based birth defects surveillance programs in the United States.* BMC Public Health, 2015. **15**: 925
126. Andersson, A., Hallberga, N., and Timpka, T., *A model for interpreting work and information*

*management in process-oriented healthcare organisations.* International journal of medical informatics (Shannon, Ireland), 2003. **72**(1): 47-56
127. Braa, J.r., Heywood, A., and Sahay, S., *Improving quality and use of data through data-use workshops: Zanzibar, United Republic of Tanzania.* Bulletin of the World Health Organization, 2012. **90**(5): 379-384
128. Bradley, H., et al., *Can the Perinatal Information System in Peru be used to measure the proportion of adverse birth outcomes attributable to maternal syphilis infection?* Revista panamericana de salud pública, 2014. **36**(2): 73-79
129. Chisha, Z., et al., *Enhanced surveillance and data feedback loop associated with improved malaria data in Lusaka, Zambia.* Malar. J., 2015. **14**(222): 222
130. Cibulskis, R.E. and Hiawalyer, G., *Information systems for health sector monitoring in Papua New Guinea.* Bulletin of the World Health Organization, 2002. **80**(9): 752
131. DiGiacomo, M., et al., *Health information system linkage and coordination are critical for increasing access to secondary prevention in Aboriginal health: a qualitative study.* Quality in Primary Care, 2010. **18**(1): 17-26
132. Galvin, S., et al., *Improving antimicrobial prescribing in Irish primary care through electronic data collection and surveillance: a feasibility study.* BMC Family Practice, 2015. **16**: 77
133. Hajdu, A., et al., *Evaluation of the national surveillance system for point-prevalence of healthcare-associated infections in hospitals and in long-term care facilities for elderly in Norway, 2002-2008.* BMC Public Health, 2011. **11**: 923-923
134. Haskew, J., et al., *Implementation of a cloud-based electronic medical record for maternal and child health in rural Kenya.* Int J Med Inform, 2015. **84**(5): 349-354
135. Haswell, M.R., et al., *Validation and enhancement of Australian Aboriginal and Torres Strait Islander psychiatric hospitalisation statistics through an Indigenous Mental Health Worker register.* Rural & Remote Health, 2013. **13**(1): 1-10
136. Heidebrecht, C.L., *Incorporating Scannable Forms into Immunization Data Collection Processes: A Mixed-Methods Study.* PloS one, 2012. **7**(12): e49627
137. Ing, S., et al., *A focus group study of enteric disease case investigation: successful techniques utilized and barriers experienced from the perspective of expert disease investigators.* BMC Public Health, 2014. **14**(1): 1-14
138. Kaposhi, B.M., Mqoqi, N., and Schopflocher, D., *Evaluation of antiretroviral treatment programme monitoring in Eastern Cape, South Africa.* Health Policy and Planning, 2015. **30**(5): 547-554
139. Kawonga, M., Blaauw, D., and Fonn, S., *Aligning vertical interventions to health systems: a case study of the HIV monitoring and evaluation system in South Africa.* Health Research Policy And Systems, 2012. **10**: 2-2
140. Kiilu, E.M., *Human resource capacity for information management in selected public healthcare facilities in Meru County, Kenya.* Pan Afr Med J, 2015. **20**: 334
141. Krenzelok, E.P., et al., *A model to improve the accuracy of US Poison Center data collection.* Clin Toxicol (Phila), 2014. **52**(8): 889-896
142. Ledikwe, J.H., et al., *Improving the quality of health information: a qualitative assessment of data management and reporting systems in Botswana.* Health Res Policy Syst, 2014. **12**(1): 1-17
143. Lowe, G.R., Griffin, Y., and Hart, M.D., *Analysis of STAT laboratory turnaround times before and after conversion of the hospital information system.* Respir Care, 2014. **59**(8): 1275-1280
144. Madsen, M., et al., *Population-based register of acute myocardial infarction: manual of operations.* Eur J Cardiovasc Prev Rehabil, 2007. **14**(Supplement 3): S3-S22
145. Melnik, T.A., *Barriers in accurate and complete birth registration in New York State.* Matern Child Health J, 2015. **19**(9): 1943-1948
146. Mphatswe, W., et al., *Improving public health information: a data quality intervention in Kwazulu-Natal, South Africa.* Bull World Health Organ, 2012. **90**(3): 176-182
147. Murai, S., et al., *Systemic factors of errors in the case identification process of the national routine health information system: A case study of Modified Field Health Services Information System in the Philippines.* BMC Health Services Research, 2011. **11**: 271
148. Mykkänen, J., et al., *A national study of eHealth standardization in Finland-goals and recommendations.* Stud Health Technol Inform, 2007. **129**(Pt 1): 469-473
149. Nicol, E., et al., *Human factors affecting the quality of routinely collected data in South Africa.* Studies In Health Technology And Informatics, 2013. **192**: 788-792
150. Paterson, B.J., et al., *Sustaining surveillance: evaluating syndromic surveillance in the Pacific.* Global Public Health, 2012. **7**(7): 682-694

151. Puttkammer, N., et al., *An assessment of data quality in a multi-site electronic medical record system in Haiti.* International Journal of Medical Informatics, 2016. **86**(Supplement C): 104-116
152. Reilly, S.H., et al., *Training and technology: improving the quality and timeliness of service plans and case documentation.* Administration in Social Work, 2011. **35**(2): 207-222
153. Rimando, M., et al., *Data collection challenges and recommendations for early career researchers.* Qualitative report, 2015. **20**(12): 2025-2036
154. Schuurman, N., et al., *Collecting injury surveillance data in low- and middle-income countries: The Cape Town Trauma Registry pilot.* Glob Public Health, 2011. **6**(8): 874-889
155. Soti, D.O., et al., *Feasibility of an innovative electronic mobile system to assist health workers to collect accurate, complete and timely data in a malaria control programme in a remote setting in Kenya.* Malar. J., 2015. **14**(1): 1-8
156. Sychareun, V., et al., *Data verification at health centers and district health offices in Xiengkhouang and Houaphanh Provinces, Lao PDR.* BMC Health Serv Res, 2014. **14**: 255
157. Tamrat, T. and Kachnowski, S., *Special delivery: an analysis of mHealth in maternal and newborn health programs and their outcomes around the world.* Maternal & Child Health Journal, 2012. **16**(5): 1092-1101
158. West, C., Farmer, J., and Whyte, B., *Implementing computerised workload data collection in rural primary health care.* Australian Journal of Rural Health, 2004. **12**(1): 11-16
159. Wilkins, K., et al., *The data for decision making project: assessment of surveillance systems in developing countries to improve access to public health information.* Public Health, 2008. **122**(9): 914-922
160. Yourkavitch, J., et al., *How do we know? An assessment of integrated community case management data quality in four districts of Malawi.* Health Policy and Planning, 2016. **31**(9): 1162-1171
161. Juran, J.M., *Juran on leadership for quality: an executive handbook*. 1989, New York, N.Y.: The Free Press.
162. World Health Organization, *World health statistics 2017: monitoring health for the SDGs, Sustainable Development Goals*. Vol. Licence: CC BY-NC-SA 3.0 IGO. 2017, Geneva Switzerland: World Health Organization.
163. Sheikhtaheri, A., *Development of a tool for comprehensive evaluation of population-based cancer registries.* International Journal of Medical Informatics (Shannon, Ireland), 2018. **117**: 26-32
164. Dufour, É., Duhoux, A., and Contandriopoulos, D., *Reliability of a Canadian database for primary care nursing services' clinical and administrative data.* International Journal of Medical Informatics, 2018. **117**: 1-5
165. Chen, H., et al., *Identification of the essential components of quality in the data collection process for public health information systems.* Health Informatics Journal, 2019: 1460458219848622
166. Grigore, B., et al., *EXPLICIT: a feasibility study of remote expert elicitation in health technology assessment.* BMC Medical Informatics And Decision Making, 2017. **17**(1): 131
167. Hitimana, R., et al., *Incremental cost and health gains of the 2016 WHO antenatal care recommendations for Rwanda: results from expert elicitation.* 2019. **17**
168. Cooke, R.M. and Shrader-Frechette, K., *Experts in Uncertainty : Opinion and Subjective Probability in Science*. 1991, Cary, UNITED STATES: Oxford University Press, Incorporated.
169. Wu, Z., et al., *HIV/AIDS in China: Epidemiology, Prevention and Treatment*, Z. Wu, et al., Editors. 2020, Springer Nature Singapore Pte Ltd: Singapore.
170. Yip, J.L.Y., et al., *Process evaluation of a National Primary Eye Care Programme in Rwanda.* BMC Health Services Research, 2018. **18**(1)
171. Lopez, A.D. and Setel, P.W., *Better health intelligence: a new era for civil registration and vital statistics?* BMC Medicine, 2015. **13**: 73
172. Le Floch, B., et al., *Which positive factors give general practitioners job satisfaction and make general practice a rewarding career? A European multicentric qualitative research by the European general practice research network.* BMC Family Practice, 2019. **20**(1): 96
173. Yu, P., et al., *Unintended adverse consequences of introducing electronic health records in residential aged care homes.* International Journal of Medical Informatics, 2013. **82**(9): 772-788
174. Cao, Z., et al., *Impact of Systematic Factors on the Outbreak Outcomes of the Novel COVID-19 Disease in China: Factor Analysis Study.* J Med Internet Res, 2020. **22**(11): e23853
175. Hall, H.I., et al., *Describing the HIV/AIDS epidemic: using HIV case data in addition to AIDS case reporting.* Annals of Epidemiology, 2005. **15**(1): 5-12

176. Wang, N., et al., *Estimating the number of people living with HIV/AIDS in China: 2003-09.* Int. J. Epidemiol., 2010. **39**(suppl 2): ii21-ii28
177. Qin, Q., et al., *Quality analysis on the direct report network for national HIV/AIDS in 2006.* Disease Surveillance, 2007. **22**(11): 769-772
178. Xu, J. and Mao, Y., *Current status and prospective of Chinese AIDS CRIMS.* Chinese Journal of AIDS & STD, 2016. **22**(9): 756-758
179. Chen, H., et al., *Validation of Four-dimensional Components for Measuring Quality of the Public Health Data Collection Process: Expert Elicitation (Preprint)*. 2019.
180. Chen, M., Liao, Q., and Cheng, H., *Investigation on the status of grass roots AIDS prevention and control human resources in Jiangxi province.* Soft Science of Health, 2017. **31**(5): 35-39
181. Yu, Y., et al., *Assessment of mental health of health workers following up people living with HIV/AIDS in Chengdu.* Chin J AIDS STD, 2019. **25**(1): 64-66+76
182. Ni, K., *Barriers and facilitators to data quality of electronic health records used for clinical research in China: a qualitative study.* BMJ open, 2019. **9**(7)
183. Wu, Z., et al., *China AIDS policy implementation: reversing the HIV/AIDS epidemic by 2015.* International Journal of Epidemiology, 2010. **39**(suppl 2): ii1-ii3
184. UWA System Health Lab. *DART tool*. 2020 [cited 2020 16 July]; Available from: https://drat-process.com.
185. ISO, *ISO 8000-61: Data quality——Part 61: Data quality management: Process reference model*. 2016, ISO.
186. Carretero, A.G., et al., *MAMD 2.0: Environment for data quality processes implantation based on ISO 8000-6X and ISO/IEC 33000.* Computer Standards & Interfaces, 2017. **54**: 139-151

# Appendix A Characteristics of methods for assessment of the three dimensions of data quality in public health information systems

This appendix contains three sub-tables used in Chapter 2. Table A1 shows the characteristics of data quality assessment methods used for assessing the quality of data in public health information systems, Table A2 methods for assessing the quality of data use, and Table A3 methods for assessing the quality of the data collection process.

**Table A1 Characteristics of methods for assessment of the data dimension reported in the 36 publications included in the review**

| Authors Year | Attributes Major measures | Study design | Data collection methods | Data analysis methods | Contribution | Limitations |
|---|---|---|---|---|---|---|
| Ancker, et al. 2011 [96] | Percentage of missing data, inconsistencies and potential errors of different variables; number of duplicate records, number of non-standardization of vocabulary, number of inappropriate fields | Quantitative audit of data attributes of dataset. | Selected one data set and used tools to query 30 variables, manually assessed data formats | Rates, percentage or counts | Identified data quality issues and their root causes. | Need a specific data query tool |
| Bosch-Capblanch, et al. 2009 [95] | Accuracy Proportions in the relevant data set, such as the recounted number of indicator's data by the reported number at the next tier in the reporting system. A ratio less than 100% | Quantitative audit of data accuracy by external auditors applying WHO DQA in 41 countries | A multistage weighted representative random sampling procedure, field visits verifying the reported data. Compared data collected from fields with the reports at the next tier | Percentage, median, inter-quartile range, 95% confidence intervals, ratio (verification factor quotient) | Systematic methodology to describe data quality and identify basic recording and reporting practices as key factors and good practices | Limited attributes, lack of verification of source of actual data and excluded non-eligible districts |

| | | | | | | |
|---|---|---|---|---|---|---|
| | indicates ‘over-reporting’; a ratio over 100% suggests ‘under-reporting’ | | | adjusted and extrapolated | | |
| CDC 2001 [59] | Completeness, accuracy Percentage of blank or unknown responses, ratio of recorded data values over true values | Quantitative audit of dataset, a review of sampled data, a special record linkage, or a patient interview | Calculating the percentage of blank or unknown responses to items on recording forms, reviewing sampled data, conducting record linkage, or a patient interview | Descriptive statistics: percentage | Provides generic guidelines | Lack of detail on procedures, needs adjustment |
| Chiba, et al. 2012 [94] | Completeness: percentage of complete data. Accuracy: percentage of the complete data which were illegible, wrongly coded, inappropriate and unrecognized. Relevance: comparing the data categories with those in upper level report to evaluate whether the data collected satisfied management information needs | Quantitative verification of data accuracy and completeness, and qualitative verification of data relevance in a retrospective comparative case study | Purposive sampling, clinical visits, re-entered and audited 30 data categories of one year data to evaluate accuracy and completeness; qualitatively examined data categories and instructions to assess the relevance, completeness and accuracy of the data, semi-structured interviews to capture factors that influence data quality | Descriptive statistics for accuracy and completeness of the data. Qualitative data were thematically grouped and analyzed by data categories, instructions, and key informants' views | Quantitative and qualitative verification of data quality; comparison of two hospitals increased generalizability of the findings | Consistency and timeliness were not assessed. Data from the system were not able to be validated |

| | | | | | | |
|---|---|---|---|---|---|---|
| CIHI 2009 [29] | Accuracy: coverage, capture and collection, unit non-response, item (partial) non-response, measurement error, edit and imputation, processing and estimation. Timeliness: data currency at the time of release, documentation currency. Comparability: data dictionary standards, standardization, linkage, equivalency, historical comparability. Usability: accessibility, documentation, interpretability. Relevance: adaptability, value. | Quantitative method, user survey-questionnaire | Questionnaire by asking users, three ratings of each construct, including met, not met, unknown or not applicable (or minimal or none, moderate, significant or unknown) All levels of the system were taken into account in the assessment | Descriptive statistics for ratings by each criterion, the overall assessment for a criterion based on the worst assessment of the applicable levels | Data quality assessed from user's perspective provides comprehensive characteristics and criteria of each dimension of data quality. 5 dimensions, 19 characteristics and 61criteria | Undefined procedures of survey including sample size. Being an internal assessment, rating scores were used for internal purposes |
| Clayton, et al. 2013 [93] | Accuracy Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) | Quantitative method to audit dataset by power calculation of 840 medical records | Two stage sampling of study sites, abstracting records and auditing 25 data variables to assess accuracy of the data reported on three data sources | Descriptive statistics were calculated for each data sources; summary measure of kappa values sing the paired | Accessing and linking three data sources—maternal medical charts, birth certificates and hospital discharge data whose access is limited and | Limited generalizability of the findings; low sample size and limited representativeness |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | sample Wilcoxon signed rank test | using the medical chart as the gold standard | |
| Corriols, et al. 2008 [92] | Under-reporting Calculating the difference between registered cases and surveyed cases | Quantitative method to administer a cross-sectional survey in the country | 4 stage consistent random sampling method across the country. Face-to-face interview questionnaire survey. | Descriptive statistics for estimation of national underreporting by using survey results | Good representativeness of the study population | Lack of case diagnosis information and the quality of the source of the data |
| Dai, et al. 2011 [107] | Under-reporting, errors on report forms, errors resulted from data entry; completeness of information, accuracy, timeliness | Qualitative and quantitative methods by reviewing publications on the system and data from the system | Reviewing publications on the system and data from the system | Descriptive statistics for quantitative data and thematically grouping for qualitative data | Evaluated all existing sub-systems included in the system | Undefined procedures of review, lack of verification of source data |
| Dixon, et al. 2011 [91] | Completeness The proportion of diagnosed cases and the proportion of fields in a case report | Quantitative method by auditing dataset | Creating a minimum data set of 18 key data elements, using structured query language (SQL) statements to calculate the percent completeness of each field of a total of 7.5 million laboratory reports | Descriptive statistics to calculate the difference between the completeness scores across samples | Development of a method for evaluating the completeness of laboratory data | Need a specific data query tool and only assessed completeness |
| Edmond, et al. 2011 [106] | Completeness, illegible hand writing, | Quantitative method: audit the submitted | 3303 cards from randomly selected five weeks from each | Descriptive statistics for the percentag | Random selection of dataset | Only calculated complet |

| | | | | | | |
|---|---|---|---|---|---|---|
| | calculation errors<br>The proportion of the consultation rates for two items, the proportion of illegible hand writing and required clarification, and the proportion of calculation errors on the submitted record forms | record forms in the dataset | year between 2003-2009 | e of each data quality attribute | | eness, without field verificati on of accuracy of data |
| Ford, et al. 2007 [90] | Accuracy<br>Sensitivity, specificity and positive predictive values | Quantitativ e method to use record linkage to audit dataset, comparing the system with a gold standard (a statewide audit dataset) | Calculated data quality indicators for 18 data variables, compared with a statewide audit (gold standard) , including 2432 babies admitted to NICUs, 1994-1996 | Descriptiv e statistics with exact binomial confidenc e intervals for data quality attributes, comparing two datasets by using the chi-square test | The findings are consistent with other validation studies that compare routinely collected population health data with medical records | Lack of verificati on of variation s between two datasets, inadequa te represen tativenes s |
| Forster, et al. 2008 [105] | Missing data<br>The percentage of the missing data | Quantitativ e method to audit dataset | Assessed data quality of a set of six key variables. A global missing data index was computed determining the median of the percentages missing data. Sites were ranked according to this index | Confidenc e interval (CI), Cronbach ’s alpha, multivaria te logic models, Spearman rank correlatio n coefficient | Directly examined associations between site characteristic s and data quality | Conveni ence sample and uncertai n generali zability |

| | | | | | | |
|---|---|---|---|---|---|---|
| Freestone, et al. 2012 [89] | Accuracy, consistency, granularity | Quantitative method to audit dataset from three components: source documents, data extraction/transposition, and data cleaning | Systematic sampling 200 cases, each geocoded and comparatively assessed of data quality with and without the influence of geocoding, by pre-selected criteria | Data quality measured by category: perfect, near perfect, poor. Paired t-test for 200 samples and chi-square test for year | Quantify data quality attributes with different factors | No reference type and no field verification (for historic data) |
| Frizzelle, et al. 2009 [88] | Accuracy, completeness, currency Assessed by positional errors, generalizations incompatible with highly accurate geospatial locations, updated with the change | Quantitative method to use geographic information systems (GIS) by developing a custom road dataset for analyzing data quality of four datasets | Developed a custom road dataset, and compared with four readily available public and commercial road datasets; developed three analytical measures to assess the comparative data quality | Percentage, concordance coefficients and Pearson correlation coefficients | Exemplary to assessing the feasibility of readily available commercial or public road datasets and outlines the steps of developing a custom dataset | No field verification for historic data |
| Hahn, et al. 2013 [98] | Completeness, accuracy The percentage of correctly or completely transmitted items from the original data source to secondary data sources | A multiple case study by quantitative and qualitative approaches in 3 antenatal care clinics of two private and one public | Quantitative method: selected 11 data tracer items followed retrospectively and audited compared to independently created gold standard. Qualitative methods: structured interviews and | Quantitative data: manual review, descriptive statistics, Kruskal-Wallis test, Mann-Whitney U test for continuou | Combining different methods and viewing the information systems from different viewpoints, covering the quality of PHIS and drawing suggestions for | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | Kenyan hospital | qualitative in-depth interviews to assess the subjective dimensions of data quality. Five-point scales were used for each statement. Purposeful sampling of 44 staff for survey and 15 staff for key informants interviews | s measures. Qualitative data: processed manually and classified and grouped by facility and staff class | improvement of data quality from qualitative results, likely to produce robust results in other settings | |
| Harper, et al. 2011 [104] | Completeness: the proportion of filled fields on the reports. Validity: the proportion of the number of the written indicators against the assigned standard; the proportion of entered incorrect numbers; the proportion of illegible entries; the proportion of entries out of chronological order | Quantitative method to audit an electronic database that was manually extracted entries of a reference syndrome from anonymized dataset from the E-Book health registry entries | Using a random systematic sample of 10% of the extracted entries (i.e. beginning with a randomly chosen starting point and then performing interval sampling to check 10% of records), with an acceptable error rate of <5% | Descriptive statistics on attributes. To avoid bias, age and sex proportions were extracted from available records, the proportions compared to National Census data. | Examine data quality using a reference syndrome, thus making it possible to provide informed recommendations. Descriptive data analysis provides grounded and useful information for decision makers | No evaluation of data collection methods |
| Hills, et al. 2012 [111] | Timeliness: the number of days between Service Date and Entry Date of submission of data to the system (three categories: ≤ 7 | Quantitative method to audit data set. | Use a de-identified 757,476 demographic records and 2,634,101 vaccination records from the system | Descriptive statistics on attributes | Large dataset provides a statistically significant association | Not able to examine two highly relevant components of data |

| | | | | | | |
|---|---|---|---|---|---|---|
| | days, = 8-30 days, and ≥ 31 days). Completeness: the complete recording of data elements by calculating the proportion of complete fields over total number of fields | | | | | quality: vaccination record coverage completeness and accuracy |
| Lash, et al. 2012 [112] | Completeness: the number of locations matching to latitude and longitude coordinates. Positional accuracy: spatial resolution of the dataset. Concordance: the number of localities falling within the boundary. Repeatability: the georeferencing methodology | Georeferencing historic datasets, quantitative method research historic data with 404 recorded MPX cases in seven countries during 1970-1986 from 231 unique localities | Develop ecological niche models and maps of potential MPX distributions based on each of the three occurrence data sets with different georeferencing efforts | Descriptive statistics on attributes and comparison of georeferencing match rates | Document the difficulties and limitations in the available methods for georeferencing with historic disease data in foreign locations with poor geographic reference information. | Not able to examine the accuracy of data source |
| Lin, et al. 2012 [103] | Completeness: sufficient sample size. Accuracy: data missing or discrepancies between questionnaires and database | Quantitative and qualitative methods, auditing data set by cross-checking 5% questionnaires against the electronic | Review guidelines and protocols using a detailed checklist; purposive sampling; direct observations of data collection; cross-checking compared database with the questionnaires | Descriptive statistics for attributes of data quality | Mixed-methods to assess data quality | Unable to generalize the findings to the whole system |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | database during the field visits | | | | |
| Litow and Krahl 2007 [102] | Accuracy, use of standards, completeness, timeliness, and accessibility | Quantitative method based on a framework developed for assessment of PHIS | Exported and queried one year data by 12 data items | Descriptive statistics for data quality attributes | Research on Navy population for public health applicability of the system and identified factors influencing data quality | Needs a framework which was undefined in the research |
| Lowrance, et al. 2007 [101] | Completeness, updated-ness, accuracy | Qualitative method by following CDC's Guidelines with qualitative methods | Standardized interviews with 18 key informants during 12 site visits, and meetings with stakeholders from government, non-governmental and faith-based organizations. | Thematically grouping interview responses | Data quality qualitatively assessed by key informants and stakeholders | Lack of quantifiable information |
| Makombe, et al. 2008 [87] | Completeness: filled fields; accuracy: no missing examined variables or a difference less than 5% compared to the supervision report | Quantitative methods to audit the quality of site reports as of the date of field supervisory visits | 6 case registration fields and 2 outcome data were examined | Descriptive statistics on attributes of data quality from site reported were compared to those of supervision reports ("gold standard") | Set up thresholds of accuracy, examine association between facility characteristics and data quality | Only assessed aggregated facility-level rather individual patient data |
| Mate, et al. 2009 [86] | Completeness: no missing data in a period of time; accuracy: | Quantitative methods to assess attributes. | Extracted one year dataset for surveying data completeness of | Descriptive statistics, by using | Large sample size, randomized sampling | Sources of data were not verified |

| | | | | | | |
|---|---|---|---|---|---|---|
| | the value in the database was within 10% of the gold standard value or percentage deviation from expected'' for each data element when compared to the gold standard data set | Completeness: surveying six data elements in one year dataset from all sample sites. Accuracy: surveying a random sample sites in three months to assess variation of three steps in data collection and reporting | six data elements. Randomization sampling. Paralleled collection of raw data by on-site audit of the original data. Reconstructed an objective, quality-assured ''gold standard'' report dataset. All clinical sites were surveyed for data completeness, 99 sites were sampled for data accuracy | charts, average magnitude of deviation from expected, and data concordance analysis between reported data and reconstructed dataset | technique, the use of an objective, quality-assured ''gold standard'' report generated by on-site audit of the original data to evaluate the accuracy of data elements reported in the PHIS. Set up thresholds of accuracy and errors | |
| Matheson, et al. 2012 [109] | Missing data, invalid data, data cleaning, data management processes | Not conducted | N/A | N/A | N/A | Lack of specific metrics |
| ME DQA 2008 [83] | Accuracy, reliability, precision, completeness, timeliness, integrity, confidentiality | Comprehensive audit in quantitative and qualitative methods including in-depth verifications at the service delivery sites; and follow-up verification | 4 methods for selection of sites including purposive selection, restricted site design, stratified random sampling, random sampling; the time period corresponding to the most recent relevant reporting period for the IS. Five types of data verifications | Descriptive statistics on accuracy, availability, completeness, and timeliness of reported data, including results verification ratio of verificatio | Two protocols, 6 phases, 17 steps for the audit; sample on a limited scale considering the resources available to conduct the audit and level of precision desired; 2-4 indicators "case by | Confined to specific disease context and standard program-level output indicators |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | s at the next level | including description, documentation review, trace and verification (recount), cross-checks, spot-checks. Observation, interviews and conversations with key data quality officials were applied to collect data | n, percentage of each dimension, differences between cross-check | case" purposive selection; on-site audit visits by tracing and verifying results from source documents at each level of the PHIS | |
| ME PRISM 2010 [78] | Relevance: comparing data collected against management information needs. Completeness: filling in all data elements in the form, the proportion of facilities reporting in an administrative area. Timeliness: submission of the reports by an accepted deadline. Accuracy: comparing data between facility records and reports, and between facility reports and administrative area databases | Quantitative method, Questionnaire survey including data completeness and transmission, data accuracy check, data collection processing and analysis, assess the respondent's perceptions about the use of registers, data collection forms and information technology | Non-anonymous interviews with identified name and title, including asking, manual counting, observation and recording results or circling 'yes or no' | Using a data entry and analysis tool (DEAT), described in quantitative terms rather than qualitative. Yes or No tick checklist | A diagnostic tool in forms measures strengths and weaknesses in three dimensions of data quality. Quantitative terms help set control limits and targets and monitor over time | Indicators are not all inclusive; tool should be adapted in a given context. Need pre-test and make adjustments |

| | | | | | | |
|---|---|---|---|---|---|---|
| Pereira, et al. 2012 [110] | Completeness and accuracy of data-fields and errors | Quantitative and qualitative methods: Use primary (multi-center randomized trial) and secondary (observational convenience sample) studies | Field visits of a sample of clinics within each PHU to assess barcode readability, method efficiency and data quality. 64 clinic staff representing 65% of all inventory staff members in 19 of the 21 participating PHUs completed a survey examining method perceptions | Descriptive statistics: a weighted analysis method, histograms, 95% confidence intervals, F-test, Bootstrap method, the two-proportion z-test, adjusted the p values using Benjamin – Hochberg's method for controlling false discovery rates (FDR) | The first study of such in an immunization setting. | Lack of representativeness to multiple lot numbers. Inaccurate data entry was not examined. Observations were based on a convenience sample |
| Petter and Fruhling 2011 [100] | Checklist of system quality, information quality | Quantitative methods to use DeLone& McLean IS success model. Use a survey in structured questionnaire | Online survey, facsimile, and mail, using 7 Likert scale for all quantitative questions. A response rate of 42.7% with representative demographics | Summative score for each construct, and each hypothesis was tested using simple regression. Mean, standard deviation, | Demonstrates the need to consider the context of the medical information system when using frameworks to evaluate the system | Inability of assessing some correlational factors due to the small PHIS user system |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | the Spearman's correlation coefficients for analysis | | |
| Ronveaux et al. 2005 [97] | Consistency The ratio of verified indicators reported compared with written documentation at health facilities and districts | Quantitative methods, using standardized data quality audits (WHO DQAs) in 27 countries | Recounted data compared to reported data | Descriptive statistics | A quantitative indication of reporting consistency and quality, facilitate comparisons of results over time or place | Similar to WHO DQA |
| Saeed, et al. 2013 [99] | Completeness, validity, data management Calculation of missing data and illegal values (out of a predetermined range), data management (data collection, entry, editing, analysis and feedback) | Quantitative and qualitative methods, including interview, consultation, and documentation review | 10 key informants interview among the directors, managers and officers; 1 or 2 staff at national level interviewed; consultation with stakeholders, document review of each system strategic plan, guidelines, manuals, annual reports and data bases at national level | Predefined scoring criteria for attributes: poor, average, or good | Comparison of two PHIS | Purposive sampling |
| Savas, et al. 2009 [85] | Sensitivity, specificity and the Kappa coefficient for inter-rater agreement | Quantitative methods: audit data set by cross-linkage techniques | Databases were deterministically cross linked using female sex and social security numbers. Deterministic and probabilistic | Descriptive statistics | Combined electronic databases provide nearly complete ascertainmen | Using data which were missing would affect the |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | linkage methods were also compared | | t for specific dataset | results by under-ascertainment |
| Van Hest, et al. 2008 [84] | Accuracy and completeness of reported cases | Quantitative methods: audit data set by record-linkage and capture-recapture techniques | Use record linkage, false-positive records and correction, and capture-recapture analysis through 3 data sources by a core set of identifiers | Descriptive statistics: number, proportion and distribution of cases, 95% ACI (Approximate confidence interval), Zelterman's truncated model | Record-linkage of TB data sources and cross-validation with additional TB related datasets improves data accuracy as well as completeness of case ascertainment | Imperfect record-linkage and false-positive records, violation of the underlying capture–recapture assumptions |
| Venkatarao, et al. 2012 [65] | Timeliness: Percentage of the reports received on time every week; Completeness: percentage of the reporting units sending reports every week | Quantitative methods: Use field survey (questionnaire) with a 4-stage sampling method | 2 study instruments: the first focused on the components of disease surveillance; the second assessed the ability of the study subject in identifying cases through a syndromic approach | Descriptive statistics analysis | Two instruments including surveying users and dataset | Not able to assess the quality of data source such as accuracy |
| WHO DQA 2003 [79] | Completeness of reporting, report availability, timeliness of reporting, verification factor | Quantitative methods to audit selected indicators in the dataset. Multi-stage sampling | Recounted data compared to reported data | Descriptive statistics | A systematic methodology to describe data quality in the collection, transmission and use of information, | Sample size and the precision dictated by logistical and |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | from stratified sample representing the country's PHIS | | | and to provide recommendations to address them | financial considerations |
| WHO DQRC 2013 [81] | Completeness of reporting; internal consistency of reported data; external consistency of population data; external consistency of coverage rates | Quantitative method to conduct a desk review of available data and a data verification component at national level and sub-national level | An accompanying Excel-based data quality assessment tool | Simple descriptive statistics: percentage, standard deviation | Easy to calculate | Needs WHO DQA to complement assessment of the quality of data source |
| WHO HMN 2008 [82] | Data-collection method, timeliness, periodicity, consistency, representativeness, disaggregation, confidentiality, data security, and data accessibility. | Quantitative and qualitative methods to use 63 out of 197 questions among around 100 major stakeholders | Use consensus development method by group discussions, self-assessment approach, individual (less than 14) or group scoring to yield a percentage rating for each category | An overall score for each question, quartiles for the overall report. | Expert panel discussion, operational indicators with quality assessment criteria. | Sample size was dictated by logistical and financial considerations |

**Table A2 Characteristics of the methods for assessment of data use reported in the 10 publications included in the review**

| Authors Year | Attributes Major measures | Study design | Data collection methods | Data analysis methods | Contribution | Limitations |
|---|---|---|---|---|---|---|
| Freestone, et al. 2012 [89] | Trends in use Actioned requests from researchers in a set period of time | Analysis of actioned requests from researchers in a period of time | Abstracted data from the database for the study period | Trend analysis of proportion of requests | Quantifiable measures | Limit attributes |
| Hahn, et al. 2013 [98] | Use of data The usage of aggregated data for monitoring, information processing, finance and accounting, and long-term business decisions | Qualitative methods: structured interviews with purposive sample of 44 staff and in-depth interviews with 15 key informants | Structured survey and key informant interview to assess five structured statements. Five-point scales were used for each statement | Responses were processed manually, classified and grouped by facility and staff class | Identified indicators of use of data | Lack of quantifiable results for assessment of data use |
| Iguiñiz-Romero and Palomino 2012 [108] | Data use Data dissemination: identify whether data used for decision making, the availability of feedback mechanisms | Qualitative exploratory study including interview and review of documentations | Open-ended, semi-structured questionnaire interviews with 15 key decision-makers. Review national documents and academic publications | Interview data recorded, transcribed, organized thematically and chronologically. The respondents were identified by positions but not named | Most respondents held key positions and a long period of the reviewed publications | Purposive sample lack of representativeness |
| Matheson, et al. 2012 [109] | Clinical use of data: the number of summaries produced. Use of data for local activities | Qualitative and quantitative methods: key informant interview, documentation | Personal interviews by phone and through internet telephony; follow up in | Descriptive statistics using charts on number of clinics using the system in a given month, | Multiple methods | Lack of verification of data source |

| | | | | | | |
|---|---|---|---|---|---|---|
| | to improve care. Data entry: the number of active sites. Report use: the percentage of active sites using prebuilt queries to produce data for each type of report in a given month over time | review, database query. | person or by email; running SQL queries against the central database. External events were identified by reviewing news reports and through personal knowledge of the authors | percentage of active clinics | | |
| ME PRISM 2010 [40] | Checklist of use of information Report production, display of information, discussion and decisions about use of information, promotion and use of information at each level | Quantitative method to complete a predesigned checklist diagnostic tool | Checklist and non-anonymous interviewing staff, asking, manual counting, observation and recording results or circling ‘yes or no’ | Two Likert score and descriptive statistics | Quantitative terms help set control limits and targets and monitor over time | |
| Petter and Fruhling 2011 [100] | System use, intention to use, user satisfaction | Quantitative methods to use DeLone & McLean IS success model. Survey respondents with a response rate of 42.7% and with representative demographics | Use an online survey in structured questionnaire with 7 Likert scale for all quantitative questions, in addition to facsimile and mail | Summative score for each construct, and each hypothesis was tested using simple regression, in addition to mean, standard deviation, the Spearman's correlation coefficients | Use is dictated by factors outside of the control of the user, and it is not a reasonable measure of IS success. The quality does not affect the depth of use | Lack of objective assessments |

| | | | | | | |
|---|---|---|---|---|---|---|
| Qazi and Al 2011 [69] | Use of data Non-use, misuse, disuse of data | Descriptive qualitative interviews | In-depth, face to face and semi structured interviews with an interview guide, 26 managers (all men, ages ranging from 26 to 49 years; selected from federal level (2), provincial (4) and seven selected districts (20) from all four provinces) | Data transcription, analysis based on categorization of verbatim notes into themes and a general description of the experience that emerged out of statements | A qualitative study allows getting close to the people and situations being studied, identified a number of hurdles to use of data | Convenience sample only one type of stakeholders has been covered. |
| Saeed, et al. 2013 [99] | Usefulness of the system Data linked to action, feedback at lower level, data used for planning, detect outbreaks, data used for the development and conduct of studies | Quantitative and qualitative methods, including interview, consultation, and documentation review | 10 key informants interview; consultation with stakeholders, document review of each system | Predefined scoring criteria for attributes: poor, average, or good | Mixed methods | Purposive sampling |
| WHO HMN 2008 [82] | Information dissemination and use, demand and analysis, policy and advocacy, planning and priority-setting, resource | Mixed methods: quantitative and qualitative. Use 10 out of 197 questions among stakeholders at national and | Use group discussions (100 major stakeholders), self-assessment approach, individual (less than 14) | An overall score for each question, quartiles for the overall report | Expert panel discussion, operational indicators with quality assessment criteria | Lack of field verification of data use |

| | | | | | | |
|---|---|---|---|---|---|---|
| | allocation, implementation and action | subnational levels | or group scoring to yield a percentage rating for each category | | | |
| Wilkinson and McCarthy 2007 [68] | Extent of data recognition and use, strategies and routines, specific uses, dissemination | Quantitative and qualitative methods to use standardized semi-structured questionnaire telephone interviews of key informants from the management teams of the system | Telephone structured questionnaire interviews of 68 key informants from the 29 out of 34 management teams of the networks. Response options for most of the questionnaire items were yes/no or five or seven point Likert and semantic differential response scales | Quantitative and qualitative analysis of survey results. Qualitative data transcribed, ordered by question number, and common themes, then content analyzed to indicate frequencies and percentages. Correlational analysis used Pearson's r for parametric data and Spearman's Rho for non-parametric data | Quantification of qualitative data | Statistical analysis is limited by the size of the sample as there were only 29 networks and 68 individual participants, statistical power to detect an effect is weak, and general trends are mainly reported. |

**Table A3 Characteristics of the methods for assessment of data collection process reported in the 16 publications included in the review**

| Authors Year | Attributes Major measures | Study design | Data collection methods | Data analysis methods | Contribution | Limitations |
|---|---|---|---|---|---|---|
| Ancker, et al. 2011 [96] | Group discussion about root causes of poor data quality and strategies for solving the problems | Qualitative method by focus group discussion | Held a series of weekly team meetings over about 4 months with key informants | Theme grouping to each data quality issue | Initiated by and related to identified poor data quality issues | Implicitly focused. Only analyzed causes not |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | involved in the data collection | | | assessed the magnitude |
| Bosch-Capblanch, et al. 2009 [95] | Quality scores Recording and reporting of data, keeping of vaccine ledgers and information system design | Quantitative method by user's survey based on WHO DQA. A multistage weighted representative sampling procedure | Questionnaire based on a series of 19 questions and observations undertaken at each level (national, district and health units) | Each question 1 point. Average score, summary score, medians, inter-quartile ranges, confidence intervals, P value, bubble scatter chart, Rho value | Combined with data quality | Implicitly focused, the number of questions surveyed was less than that of the WHO DQA |
| CIHI 2009 [59] | Metadata documentation Data holding description, methodology, data collection and capture, data collection processing, data analysis and dissemination, data storage, and documentation. | Quantitative method by surveying users | Questionnaire | Undefined | 7 categories, with subcategories and definition and/or example | Implicitly focused |
| Corriols, et al. 2008 [92] | Identification of underreporting reasons by reviewing information flow chart and non-reporting in physicians | Qualitative method to review documentations | Review the national reports on the system related to deficiency in the information flow chart and non-reporting in physicians | Undefined | Initiated by identified data quality issues | Implicitly focused |

| | | | | | | |
|---|---|---|---|---|---|---|
| Dai, et al. 2011 [107] | Data collection, data quality management, statistical analysis and data dissemination | Qualitative method, review documentations | Document review | Theme grouping | Desk review | Implicitly focused |
| Forster, et al. 2008 [105] | Routine data collection, training and data quality control | Quantitative method by online survey | Questionnaire | Descriptive statistics. | Examine associations between site characteristics and data quality | Implicitly focused. Convenience sample |
| Freestone, et al. 2012 [89] | Data collection and recording processes | Qualitative method to review current processes about identification, code, geocode of address or location data. Staff consulted to establish and observe coder activities and entry processes | Review the processes; consultation with staff; observation of coder activities and entry processes to identify any potential cause of errors which then grouped thematically | Thematically grouping data | Identify each of the key elements of the geocoding process are factors that impact on geocoding quality | Differences in software and system settings need to be aware of. |
| Hahn, et al. 2013 [98] | Data flow: The generation and transmission of health information | Qualitative method to use workplace walkthroughs on 5 subsequent working days at each site | Informal observations of the generation and transmission of health information of all kinds for the selection of data flows | Undefined | Observation of walkthroughs | Undefined indicators |
| Iguiñiz-Romero and | Data flow or data collection process: data collectors, frequencies, data | Qualitative exploratory study including interview and | Open-ended, semi-structured questionnaire interviews with 15 key decision- | Data recorded, transcribed, organized | Most respondents held key positions and a long | Purposive sample |

| | | | | | | |
|---|---|---|---|---|---|---|
| Palomino 2012 [108] | flow, data collection processing and sharing, | review documentations | makers. Review national documents and academic publications | thematically and chronologically | period of reviewed publications | |
| Lin, et al. 2012 [103] | Data collection and reporting | Qualitative methods based on CDC's Guidelines | Review guidelines and protocols using a detailed checklist; direct observation; focus group discussions and semi-structured interviews | Theme grouping | Field visits or observations of data collection to identify impact on the data quality | Undefined indicators |
| ME DQA 2008 [83] | Five functional areas: M&E structures, functions and capabilities, indicator definitions and reporting guidelines, data collection and reporting forms and tools, data management processes, and links with national reporting system | Quantitative and qualitative methods by 13 system assessment summary questions based on 39 questions from five functional areas. Score the system combined with a comprehensive audit of data quality | Off-site desk review of documentation provided by the program/project; on-site follow-up assessments at each level of the IS, including observation, interviews, and consultations with key informants | Using summary statistics based on judgment of the audit team. Three-point Likert scale to each response. Average scores for per site between 0-3 continuous scale | DQA protocol and system assessment protocol | Implicitly focused. The scores should be interpreted within the context of the interviews, documentation reviews, data verifications and observations made during the assessment. |

| | | | | | | |
|---|---|---|---|---|---|---|
| ME PRISM 2010 [78] | Processes: Data collection, transmission, processing, analysis, display, quality checking, feedback | Quantitative method by questionnaire survey including data transmission, quality check, processing and analysis and assessing the respondent's perceptions about the use of registers, data collection forms and information technology | Non-anonymous interviewing staff with identified name and title, including asking, observation and circling 'yes or no' | Using a data entry and analysis tool (DEAT), described in quantitative terms rather than qualitative. Yes or No tick checklist | A diagnostic tool. Quantitative terms help set control limits and targets and monitor over time | Indicators are not all inclusive; tool should be adapted and pre-test and make adjustments |
| Ronveaux et al. 2005 [97] | Quality index (QI) Recording practices, storing/reporting practices, monitoring and evaluation, denominators used at district and national levels, and system design at national level | Quantitative and qualitative methods by external on-site evaluation after a multi-stage sampling based on WHO DQA. | Questionnaires and observations. Survey at national level (53 questions), district level (38 questions) and health-unit level (31 questions). Observations to workers at the health-unit level. They were asked to complete 20 hypothetical practices. | Descriptive statistics (aggregated scores, mean scores): 1 point each question or task observed. Correlational analysis by zero-order Pearson correlation coefficients | | Implicitly focused. The chosen sample size and the precision of the results were dictated by logistical and financial considerations |
| Venkatarao, et al. 2012 [65] | Accuracy of case detection, data recording, data compilation, | Quantitative method by using a 4-stage sampling method to | Questionnaires of 2 study instruments: the first focused on the components of disease | Descriptive statistics analysis | Assessment from user's viewpoint. | Implicitly focused. Lack of field verificat |

| | | | | | | |
|---|---|---|---|---|---|---|
| | data transmission | conduct field survey (questionnaire) during May-June 2005 among 178 subjects | surveillance; the second assessed the ability of the study subject in identifying cases through a syndromic approach | | | ion of data collectio n process |
| WHO DQA 2003 [81] | Quality questions checklist, quality index Five components: recording practices, storing/reporting practices, monitoring and evaluation, denominators, system design (the receipt, processing, storage and tabulation of the reported data) | Quantitative and qualitative method using questionnaire checklists for each level (three levels: national, district, health unit level) of the system including 45, 38, 31 questions respectively | Questionnaires and discussions. Observations by walking around the health unit for field observation to validate the reported values | Percentag e of the items answered yes. The target is 100% for each componen t | Describe the quality of data collection and transmissio n | Implicitl y focused. The chosen sample size was dictated by logistica l and financial consider ations |
| WHO HMN 2008 [82] | Data management or metadata A written set of procedures for data management including data collection, storage, cleaning, quality control, analysis and presentation for users, an integrated data warehouse, a metadata dictionary, | Mixed methods: quantitative and qualitative. Use 5 out of 197 questions, at various national and subnational levels | Use group discussions around 100 major stakeholders, self-assessment approach, individual (less than 14) or group scoring to yield a percentage rating for each category | An overall score for each question, quartiles for the overall report | Expert panel discussion, operational indicators with quality assessment criteria | Lack of field verificat ion of data collectio n process |

| | |
|---|---|
| | unique identifier |
| | codes available |

# Appendix B The 4D Component Framework for measuring the quality of the data collection process for public health information systems (PHIS)

This appendix contains details of 16 subcomponents and the corresponding 116 indicator statements for each of the four dimensions of the 4D framework. The 82 facilitators of the 116 indicator statements in the table are not shaded while the 34 barriers are given by light brown shading. There are two numbers in each parenthesis, the former representing the facilitator and the latter the barrier.

Table B 1 Indicators, including facilitators and barriers, in each sub-dimension of the 4 dimensions of the quality framework of the data collection process for public health information systems.

| **Dimension 1. Data Collection Management (28, 13)** | |
|---|---|
| Subcomponent | **Indicator statement** |
| Data collection protocol (16, 7) | 1. Data collection protocol is needed to guide data collection which is aim-focused, operable, and clearly understandable for frontline data collectors.<br>2. Data collection protocol can be an interpretive guidance or manual including data collection form, data definitions, guidelines on collating/aggregating data, data auditing procedures, as well as other steps of data collection, handling, analysis, and reporting.<br>3. A standardized and uniform data collection form should be used by all data collectors.<br>4. Data collection form is clear, readable, comprehensive, and unambiguous.<br>5. The reporting form is based on the WHO guidelines, and is designed to fit in one page for ease of use.<br>6. Availability of definitions and requirements of data item at the back of) data collection forms for data collectors to verify.<br>7. Have a unique number for each form and register, along with an accurate document version number to eliminate confusion.<br>8. The wording of the questions including the options to the multiple-choice questions must be accurate, direct, understandable and answerable.<br>9. The number of questions should be suitable and controlled within the allotted data collection time.<br>10. The questions for data collection are within ethical consideration.<br>11. Data collection methods are well developed, uniform, applicable and implementable.<br>12. The logbooks are kept at the health facilities for convenience of reference.<br>13. Consult with the local users of the forms and tools to integrate their input in designing and revising data items and data collection methods.<br>14. Perform data back-up regularly. |

| | |
|---|---|
| | 15. Data collection is integrated into routine data flow.<br>16. The observed differences between data collection methods are expected in certain circumstances. |
| | 1. Different report format leads to duplication and unnecessary complexity.<br>2. The requirements located at the back of a form are often 'overlooked' in form processing.<br>3. The collected data lack adequate precision for meaningful interpretation.<br>4. The data collection tools are frequently changed.<br>5. The numerator and denominator of an indicator is from different sources.<br>6. Notebooks are used instead of the standardized tools.<br>7. Differences in purpose, resources, methods, and data assessment among programs. |
| Quality assurance (12, 6) | 1. Conduct a pilot to assess the need, instrument and procedure of data collection.<br>2. Each data collection facility maintains an independent quality assurance program to ensure data accuracy.<br>3. Designated unit or full-time, experienced data clerks or registrars to audit data.<br>4. Key monitoring, evaluation and data management responsibilities at the national level are defined.<br>5. Have independent data auditor.<br>6. A single page data summary is configured as part of the PHIS application to prevent data elements from missing during data transmission.<br>7. An automatic quality assurance/quality control system to identify duplications, discrepancies, outliers, and data entry errors.<br>8. Site-specific data quality reports are automatically sent to the corresponding clinics for necessary verification.<br>9. A minimum of 20% of the submitted records are randomly selected and all the data elements are verified by a staff member other than the initial data collector each month.<br>10. The cycle from the initiation of data collection at the source data site to confirmation of receiving information from the relevant data storage site is completed consistently and timely in the maximum of three months duration.<br>11. Availability of a diverse range of data quality assurance mechanisms including regular (such as quarterly) supervision, scorecard, data verification via phone call.<br>12. Ensure logic, integrity, reliability, completeness, timeliness, accuracy, no under-reporting of data. |
| | 1. No clearly identified and uniform mechanisms to address data quality challenges.<br>2. Data management responsibilities are not clearly assigned. |

| | |
|---|---|
| | 3. A lack of ownership of tasks for data quality monitoring and evaluation, limited human resources for execution.<br>4. Lack standard way of tracking or reporting completeness regarding coverage of the data collection organizations.<br>5. No data cleaning.<br>6. The data audit reports submitted to the national level do not contain information about the reporting unit. |
| | **Dimension 2. Data Collection Environment (28, 10)** |
| Subcomponent | **Indicator statement** |
| Leadership<br>(7, 2) | 1. Management has a clear roadmap for the assignment and execution of the tasks before the job starts.<br>2. During data collection, the management has strong capabilities to pushing the job forward and ensuring the data collection procedures follow the required standard.<br>3. The management has power to issue policies, clarify and assign duty and tasks, and provide financial and material support.<br>4. The managers are professionals with good understanding about the importance of the data collection tasks and recognizing the contribution of the involved staff.<br>5. Contribution of data collection personnel is recognized in terms of cost reimbursement or appraisal.<br>6. Decentralizing leadership.<br>7. Regular supportive supervision visits to districts and facilities. |
| | 1. Limited human and financial resources.<br>2. Lack of understanding about the importance of data collection and not attending supervision/auditing/training/meeting organized by the CDC. |
| Training<br>(6, 1) | 1. Provide standardized, systematic, targeted, and mandatory training sessions.<br>2. Training is focused on operational skills and knowledge for field data collection including the definition of data to be collected, data collection methods and procedures, and communication skill.<br>3. Conduct training needs assessment to identify health workers' training needs for information management on an annual basis.<br>4. An expertise task force is formed, and its recommendations are incorporated into the training program.<br>5. Provide effective, multi-mode training including interactive, problem-solving and on-line sources.<br>6. Provide continuous, high-quality, on-job training and mentoring after the initial induction and competence assessment. |
| | 1. Inadequate training on information management. |

| | |
|---|---|
| Funding<br>(5, 1) | 1. Dedicated clerk to enter data for healthcare providers to reduce data management cost.<br>2. Investment in specific sentinel clinic sites can provide data assurance.<br>3. Funding for devices and vehicles.<br>4. Funding to enable comprehensive data collection.<br>5. Compensation for participants. |
| | 1. Limited human resources and financial constrain may impede the implementation and maintenance of information technology infrastructure, such as server and network in a clinic. |
| Organizational policy<br>(3, 4) | 1. Availability of policies ensuring sufficient funding, human resource and material support.<br>2. Embody effective management and coordination.<br>3. Built-in reward and bonus schemes to incentivize data collection activities. |
| | 1. Data collection was set up as a part-time job.<br>2. Narrow workspace insufficient for data collection.<br>3. Increased workloads did not have more funding.<br>4. The culture of 'eating big-pot rice'. |
| High-level management support<br>(4, 1) | 1. Superior provides assurance including funding, policy, training, materials, reward and punishment schemes.<br>2. Certain level of autonomy placed on data collectors.<br>3. Importance attached to a data collection task grows with the increase of superior's attention to the task.<br>4. Superiors clarify the workflow and responsibilities instead of only assigning tasks. |
| | 1. The more layers between superiors and frontline data collection facilities, the more difficult to execute the data collection tasks. |
| Collaboration among parallel organization<br>(2, 1) | 1. Parallel organizations should coordinate, cooperate, and facilitate with data collection.<br>2. A centralized organization to coordinate parallel organizations. |
| | 1. Quality of the data collected by parallel organizations, if without centralized coordination, can be poor. |
| | **Dimension 3. Data Collection Personnel (17, 5)** |
| Subcomponent | **Indicator statement** |

| | |
|---|---|
| Perception of data collection (3, 3) | 1. High acceptability of the data collection system and its data among data collection personnel.<br>2. Responsibility/commitment and level of engagement of data collectors.<br>3. Dedication to data integrity. |
| | 1. Data accuracy is just as important as data users treating patients.<br>2. Data collectors do not have ownership of data collection tasks and do not treat the task as their job responsibility.<br>3. Data-related activities are often compromised due to high-time commitment and other competing priorities. |
| Skill and Competence (5, 0) | 1. Have a competence-based framework listing the desired skill mix for data management.<br>2. Have received initial and ongoing training on basic knowledge of data collection and have contextual information.<br>3. Have clear strategies to collect data including contacting the client, using the client-request alternative contact numbers, addressing cultural and language barriers.<br>4. Have ability to check data accuracy.<br>5. In addition to expertise, competence is multi-faceted including abilities of communication, organization, coordination, and writing. |
| Communication (5, 0) | 1. Confidentiality is thoroughly explained to the case.<br>2. Be empathetic, allow clients to tell their stories, and conduct interview in a conversational style.<br>3. Sense and respect the language and cultural identity of the client.<br>4. Establish rapport and ease client anxiety.<br>5. Have strategies to address cultural and language barriers with the client. |
| Staffing pattern (4, 2) | 1. Address challenges related to lacking trained staff to carry out quality assurance responsibilities.<br>2. Have dedicated data entry clerks to collect data instead of clinical staff.<br>3. Publish clearly defined schedule and tasks to ensure that all the tasks are carried out appropriately.<br>4. Have adequate staff to cover all responsibilities, including monitoring and evaluation to improve data quality. |
| | 1. High staff turnover causes missing data or inaccurate data.<br>2. Most positions for data collection are project-funded and fixed-term appointment, lacking dedicated human resources. |
| | **Dimension 4. Data Collection System (10, 6)** |

| Subcomponent | **Indicator statement** |
|---|---|
| Functions<br>(4, 1) | 1. The data collection system needs to be designed to be easy for use and without burden on health facilities.<br>2. Allow entry of free text data considered useful and relevant by data collectors.<br>3. Automatic functions are available for data logic check, aggregation, extraction and analysis.<br>4. Use smart and advanced technology such as drop-down menus, cloud-based system, and computerized point-of-care health information systems. |
| | 1. Poor system flexibility prohibiting reporting of exceptional events; system irresponsive to changing needs of decision makers. |
| Integration of different systems<br>(2, 2) | 1.Compatible record linkage and integration are available between different data collection systems.<br>2. Data collection system is comprehensive in work functions and geographic distribution. |
| | 1. Data collection systems are incomplete, not integrated and unreliable. This creates the burden of a double data entry and reporting when data are captured in both paper-based and electronic systems.<br>2. Extensive use of multiple vertical or parallel data reporting systems. |
| Technical support<br>(2, 1) | 1. Mentors and supervisors assist data collection in addition to providing clinical support.<br>2. Dedicated person to provide technical support for data entry including data auditing, error report, and correction. |
| | 1. Poor and insufficient IT support, which is inadequate for maintaining and updating the data collection system. |
| Devices<br>(2, 2) | 1. Use computers to collect data.<br>2. Devices are compatible with the data collection system, enabling the system to be fully equipped, fast, stable, accessible and usable. |
| | 1. Lack standard practices for storage and maintenance of source documents or data in accordance with any confidentiality guidelines.<br>2. Lack policy guidance on duration of data storage and the frequency of data back-up to protect against data loss. |

# Appendix C Statement of contribution of collaborating authors

This thesis is prepared in the style of Thesis by Compilation by the University of Wollongong.

Seven articles are included in this thesis. I am the first author of all these papers. Four co-authors are involved in the publications. They are Ping Yu, David Hailey, Tingru Cui, and Ning Wang. Their percentage of contribution is indicated in the publications listed below.

This is followed by the signed co-author contribution declaration form.

**Published peer-reviewed journal articles:**

1. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Ning Wang (1%).

A review of data quality assessment methods for public health information systems, International Journal of Environmental Research and Public Health, 2014, 11(5), pp. 5170-5207

2. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Tingru Cui (1%).

Identification of the essential components of quality in the data collection process for public health information systems. Health Informatics Journal, 2019: 1460458219848622. doi:10.1177/1460458219848622.

**Articles under review by peer-reviewed journals:**

3. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Tingru Cui (1%).

Validation of four-dimensional components for measuring quality of the public health data collection process: expert elicitation

4. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Tingru Cui (1%).

Application of a four-dimensional framework to evaluate the quality of AIDS data collection process in China

**Published peer-reviewed book chapter:**

5. Hong Chen (78%), Ping Yu (20%), Ning Wang (2%).

Do we have the reliable data? An exploration of data quality for AIDS information system in China. Studies in Health Technology and Informatics 2013, 192(1-2), pp. 1042

6. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Ning Wang (1%).

Methods for assessing the quality of data in public health information systems: A critical review, Studies in Health Technology and Informatics 2014, 204, pp. 13-18

7. Hong Chen (68%), Ping Yu (20%), David Hailey (11%), Tingru Cui (1%).

Data quality of the Chinese National AIDS information system: A critical review, Studies in Health

Technology and Informatics 2017, 245, pp. 1352

**Statement of contribution of collaborating authors**

I agree that Hong Chen made the contribution to the authorship and research of paper(s) on which I am a co-author, as stated in the Statement of authorship.

| | | | |
|---|---|---|---|
| Name: | Ping Yu | Name: | David Hailey |
| Date: | July 27, 2020 | Date: | July 27, 2020 |
| Signature: | | Signature: | |
| Name: | Tingru Cui | Name: | Ning Wang |
| Date: | July 30, 2020 | Date: | July 29, 2020 |
| Signature: | | Signature: | |